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MODELING NATIONAL DECARBONIZATION CAPABILITIES USING KOHONEN MAPS

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This study sought to develop a method to cluster countries based on their decarbonization capabilities and to determine how these nations' reduction of carbon dioxide (CO_2) emissions has evolved over time. CO_2 emissions clusters were identified using 11 indicators that measure both direct and indirect CO_2 emissions, differentiating countries by their economic and population growth, energy consumption, and CO_2 emission level. The panel data included 39 countries over the 10-year period of 2012–2021. The clustering was based on such type of neural networks as Kohonen self-organizing maps. This type of model facilitated grouping countries by similar decarbonization capabilities and economic development. The findings reveal that Norway and Sweden are the leaders in creating climate-resilient economies among the 39 countries analyzed. The analysis carried out can help other countries establish benchmarks for improving their own internal decarbonization activities based on leader nations' strategies and borrowing their best practices for more efficient results. This study thus contributes to the literature regarding decarbonization activities by offering a multi-country dynamic clustering method using Kohonen maps.

Keywords: *carbon dioxide (CO_2), emission target, decarbonization, clustering, self-organizing map, neural network*

JEL Classification: C45, C53, Q53, Q56

Introduction

Countries that adopted the Paris Agreement in 2015 have set as their main priorities climate change policies and decarbonization activities that necessarily involve all domestic markets' participants. Multiple countries around the world are, therefore, accelerating the transition toward decarbonization and sustainable growth.

In 2021, economic recovery (i.e., based on purchasing power parity) increased by 5.9% for the G20, which represents around 80% of global energy consumption. This growth included a 5% rebound effect on energy consumption and 5.9% carbon dioxide (CO_2) emissions from energy combustion [1]. Thus, achieving climate neutrality will require stronger international cooperation. Domestic firms from the industry and service sectors need to move toward operating more fully in sustainable value chains at the local, national, European, and international level to increase these companies' resilience and competitiveness and to achieve decarbonization targets [2]. However, this transition could become more challenging due to energy prices and the potential risks of adjusting to regulations and market demands.

In this context, researchers must examine countries' basic capacity for decarbonizing their economy, including tracking their progress using effective management and mathematical tools and measurement instruments. Monitoring mechanisms need to be developed that can identify current and future levels of CO_2 emission reduction and explore potential opportunities for expanding decarbonization potential. Although these tools have become increasingly important, they have not been adequately addressed by the existing literature.

Previous studies [3-7] have highlighted that decreasing CO_2 emissions is the primary mitigating factor for climate change. Electricity consumption can be viewed as a major indicator of each nation's development [8], yet economic growth and increased human well-being worldwide has put pressure on expendable resources and exacerbated climate change [9]. Environmental damage has also increased due to intensified energy use, urbanization, and trade [10-13].

A few researchers have applied econometric approaches to analyzing the relationship between agricultural production [14, 15], energy consumption [16-19], international trade [20, 21], and environmental pollution. Some recent studies have also emphasized the advantages of deep learning and utilized data mining techniques to achieve natural data partitioning. The latter methods include clustering, which can deal with huge amounts of data based on unsupervised machine learning. Cluster analysis is an important tool for exploratory data processing focused on summarizing information's main characteristics [22-23]. Clustering has been successfully used in varied areas, such as finance [24-26], energy use [27, 28], and CO_2 emission levels [29].

Gong et al. [27] applied a clustering method to detect provinces with cleaner energy production in China. The selected technique also facilitated the identification of provinces' efforts to introduce cleaner energy production. Csereklyei et al. [28], in turn, used model-based clustering to examine the energy profiles and paths of states participating in Australia's National Electricity Market between 2011 and 2019, thereby defining 25 distinct electricity generation clusters.

In addition, Inekwe et al. [29] identified clusters based on 72 countries' CO_2 emissions. They have used three key determinants affecting CO_2 emissions (non-renewables, population, and real GDP) and established that in most cases, a 2-cluster solution appears to be optimal. Input variables for clustering have included non-renewable (i.e., total coal, gas, and oil use) and renewable energy consumption (i.e., total hydro, wind, solar, geothermal, marine, waste, solid waste, and liquid and gaseous biofuel-derived energy).

Previous studies have been subject to significant limitations. The latter have comprised targeting a single country (e.g., China [27] and Australia [28]), having a limited focus [27, 28], or neglected time factors (i.e., dynamic impacts) [29], including variable consumption of renewable and non-renewable energy. Prior research has thus neglected to determine CO_2 emission levels for groups of countries using a dynamic approach and to assess each nation's CO_2 emissions systematically over time.

To address these gaps, the current study sought to develop a classification of countries based on their target CO_2 emission levels for 2012–2021. Two research questions were addressed:

1. What are the main country clusters based on national target CO_2 emission levels?

2. How has each country's classification changed over time, with Ukraine serving as an example?

The following tasks were undertaken to achieve this study's main goals:

1. Define and analyze the database for each nation to identify the indicators that have had an impact on CO_2 emission levels over the 10-year period.

2. Validate the list of indicators that affect CO_2 emissions for the countries analyzed.

3. Conduct cluster segmentation and examine examples of national CO_2 emission levels.

4. Analyze each cluster's traits by determining which clusters contain ecologically friendly countries and examining how Ukraine's position has changed over the analyzed period.

The next section presents the methodology (i.e., secondary data analysis and clustering method). The results section is organized around the findings for specific countries. The final section provides the main conclusions organized by research question.

Methodology

Research design

This study started by collecting secondary data from open sources providing information on factors that affect CO_2 emission levels. Different databases were compared, including the World Bank's World Development Indicators [30], United Nations Statistics Division [31], United Nations Framework Convention on Climate Change [32], International Renewable Energy Agency [33], and Eurostat [34], as well as Enerdata's [35] interactive data tool. Given the panel data available, the present research opted to rely on two sources. The first was Enerdata's World Energy & Climate Statistics – Yearbook 2022 online application [35] for energy and CO_2 emission data, which was used to cluster countries according to their target CO_2

emission levels. The second source was the World Bank's World Development Indicators database [30], which supported the current study's analysis of economic and demographic data.

Each country's target CO_2 emission level was determined by gathering data on characteristics (i.e., indicators) that affect emissions in different countries. The literature review highlighted three sets of indicators that have been found to have a strong influence on each country's identification of a CO_2 emission target. The first set includes economic and population growth factors (e.g., real GDP per capita growth and urban population). Urbanization is a key variable that stimulates economic development through varied social and structural reforms. This study focused on dynamic change factors, so real GDP per capita growth was also selected.

The second set of indicators encompasses primary energy consumption products and energy transformation. These measures include energy intensity per unit of GDP, electricity consumption, electrification, renewables' share of electricity production, wind and solar power's share of electricity production, and coal, lignite, oil product, and natural gas consumption. Oil product consumption has a stronger direct impact on countries' internally generated CO_2 emissions than oil production does.

This research concentrated on decarbonization at the national level, so external consumption and production were excluded from the panel data. Total primary energy consumption was also removed to avoid double counting because energy product consumption is part of total energy consumption. In addition, electricity production corresponds to gross production and includes both public production (i.e., private and public electricity utilities' production) and industrial production (i.e., for the utilities' own uses) [35]. Electrification and electricity consumption pollute but to a different degree, so both determining factors had to be included.

The third set of indicators is related to greenhouse gas (GHG) emissions. These measures provide information about emissions from energy combustion (i.e., >80% of CO_2 emissions) and, in particular, the average CO_2 emission factor.

The sample under analysis was limited to 39 countries as the selected databases provided full, comprehensive, and updated information (i.e., key energy and climate statistics) about these nations, with minimal data gaps. As mentioned previously, the data on indicators from the first subset were obtained from the World Bank's World Development Indicators database [30]. Data for the last two indicator sets were collected from Enerdata's World Energy & Climate Statistics – Yearbook 2022 interactive online application [35].

Data analysis

A comprehensive table of data for the 39 countries selected for analysis contains 11 indicators' normalized values ranging from 0 to 1 (i.e., 0 = indicator's smallest value; 1 = largest value), as shown in Table 1. The proposed list of indicators can be reduced during data analysis if a specific measure fails to have a significant impact on the clustering process (i.e., indicator values more or less evenly distributed across different clusters).

Table 1

PORTION OF DATABASE ON INDICATORS OF CARBON DIOXIDE (CO_2) EMISSION LEVELS

Indicators / Countries	Energy intensity per unit of GDP	Oil product domestic consumption	Natural gas domestic consumption	Electricity consumption	Renewables share of electricity	Wind/solar power share of electricity	Average CO_2 emission factor	GDP per capita growth (annual %)	Urban population (% of total population)	Coal and lignite domestic consumption	Electrification
Algeria	0.3	0.0	0.0	0.0	0.0	0.0	0.7	0.5	0.6	0.0	0.2
Argentina	0.2	0.0	0.1	0.0	0.2	0.0	0.6	0.1	0.9	0.0	0.4
Australia	0.4	0.1	0.0	0.0	0.1	0.2	0.9	0.5	0.8	0.0	0.5
Belgium	0.3	0.0	0.0	0.0	0.1	0.3	0.5	0.4	1.0	0.0	0.4

Indicators / Countries	Energy intensity per unit of GDP	Oil product domestic consumption	Natural gas domestic consumption	Electricity consumption	Renewables share of electricity	Wind/solar power share of electricity	Average CO_2 emission factor	GDP per capita growth (annual %)	Urban population (% of total population)	Coal and lignite domestic consumption	Electrification
Brazil	0.2	0.2	0.0	0.1	0.8	0.0	0.4	0.4	0.8	0.0	0.4
Canada	0.7	0.1	0.1	0.1	0.6	0.1	0.6	0.4	0.7	0.0	0.5
Chile	0.2	0.0	0.0	0.0	0.4	0.0	0.6	0.8	0.8	0.0	0.4
China	0.8	0.6	0.2	1.0	0.2	0.1	0.9	1.0	0.3	1.0	0.4
Colombia	0.0	0.0	0.0	0.0	0.8	0.0	0.6	0.6	0.7	0.0	0.4
Czech	0.4	0.0	0.0	0.0	0.1	0.1	0.7	0.3	0.6	0.0	0.4
Egypt	0.2	0.0	0.1	0.0	0.1	0.0	0.7	0.3	0.2	0.0	0.4
France	0.2	0.1	0.1	0.1	0.2	0.2	0.3	0.3	0.7	0.0	0.5
Germany	0.2	0.1	0.1	0.1	0.2	0.5	0.7	0.4	0.7	0.1	0.4
India	0.4	0.2	0.1	0.2	0.2	0.1	0.7	0.7	0.0	0.2	0.3
Indonesia	0.2	0.1	0.1	0.0	0.1	0.2	0.6	0.8	0.3	0.0	0.2
Italy	0.1	0.1	0.1	0.1	0.3	0.6	0.7	0.0	0.6	0.0	0.4
Japan	0.2	0.3	0.2	0.2	0.1	0.1	0.8	0.5	0.9	0.0	0.6
Kazakhstan	0.8	0.0	0.0	0.0	0.1	0.0	1.0	0.6	0.4	0.0	0.3
Malaysia	0.4	0.0	0.1	0.0	0.1	0.0	0.8	0.7	0.6	0.0	0.5
Mexico	0.2	0.1	0.1	0.1	0.1	0.1	0.7	0.5	0.7	0.0	0.4
Netherlands	0.2	0.0	0.1	0.0	0.1	0.2	0.6	0.2	0.9	0.0	0.3
New Zealand	0.4	0.0	0.0	0.0	0.7	0.8	0.4	0.5	0.8	0.0	0.5

Countries \ Indicators	Energy intensity per unit of GDP	Oil product domestic consumption	Natural gas domestic consumption	Electricity consumption	Renewables share of electricity	Wind/solar power share of electricity	Average CO_2 emission factor	GDP per capita growth (annual %)	Urban population (% of total population)	Coal and lignite domestic consumption	Electrification
Nigeria	0.6	0.0	0.0	0.0	0.2	0.0	0.0	0.5	0.2	0.0	0.0
Norway	0.3	0.0	0.0	0.0	1.0	0.0	0.3	0.5	0.7	0.0	1.0
Poland	0.3	0.0	0.0	0.0	0.1	0.1	0.9	0.5	0.4	0.0	0.3
Portugal	0.1	0.0	0.0	0.0	0.4	1.0	0.6	0.0	0.5	0.0	0.5
Romania	0.2	0.0	0.0	0.0	0.3	0.2	0.6	0.6	0.3	0.0	0.3
Russia	0.8	0.2	0.6	0.2	0.2	0.0	0.6	0.7	0.6	0.1	0.3
Saudi Arabia	0.4	0.1	0.1	0.1	0.0	0.0	0.7	0.5	0.8	0.0	0.3
South Africa	0.7	0.0	0.0	0.0	0.0	0.0	1.0	0.4	0.5	0.0	0.6
Spain	0.1	0.1	0.0	0.1	0.3	0.9	0.6	0.1	0.7	0.0	0.5
Sweden	0.3	0.0	0.0	0.0	0.6	0.2	0.1	0.2	0.8	0.0	0.7
Thailand	0.4	0.1	0.1	0.0	0.1	0.0	0.5	1.0	0.2	0.0	0.3
Turkey	0.1	0.0	0.1	0.0	0.3	0.1	0.8	0.6	0.6	0.0	0.4
Ukraine	1.0	0.0	0.1	0.0	0.1	0.0	0.7	0.4	0.6	0.0	0.3
United Arab Emirates	0.4	0.0	0.1	0.0	0.0	0.0	0.8	0.5	0.8	0.0	0.3
United Kingdom	0.1	0.1	0.1	0.1	0.1	0.3	0.7	0.4	0.8	0.0	0.4
United States	0.4	1.0	1.0	0.9	0.1	0.2	0.7	0.5	0.7	0.2	0.5
Uzbekistan	1.0	0.0	0.1	0.0	0.1	0.0	0.8	0.9	0.3	0.0	0.2

Note. GDP – gross domestic product.

The literature review revealed that data mining techniques have become a quite popular method of estimating CO_2 emission levels. In addition, clustering is one of the most common methods used to find hidden patterns in sets of explanatory variables. The items belonging to each cluster are more similar to each other than to those belonging to other clusters. The artificial neural network technique was selected to cluster countries by their CO_2 emission levels for the present study.

This research's objectives required a classification of the selected nations by their potential ability to reduce CO_2 emissions. The Kohonen self-organizing map (SOM) toolkit [36, 37] was selected since it can form homogeneous groups of items and it is considered to be a convenient visual analysis tool for clustering. SOMs are used to classify items and visualize low-dimensional representations of high-dimensional data.

These maps' main feature versus other clustering methods is SOMs' ability to identify an item immediately compared to other approaches based on a specific attribute — locating best and worst items on opposite sides of the map [36, 37]. Kohonen maps are a visual representation of a two-dimensional net of neurons reflecting the organization of the data under analysis (see Fig. 1).

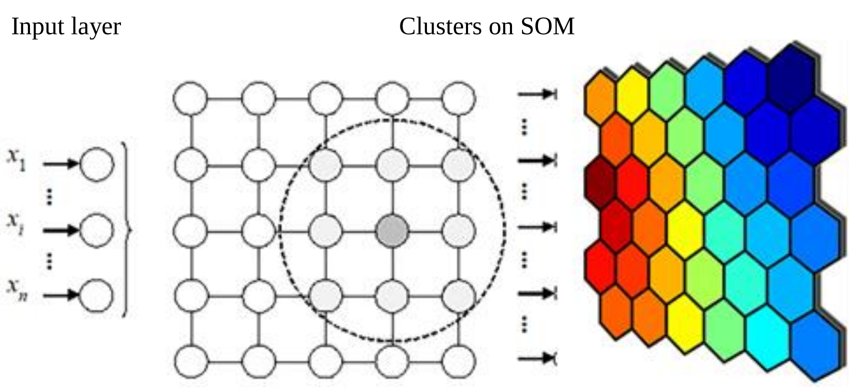

Fig. 1. Visual representation of clusters in Kohonen map [38]

In the present study, clusters of similar countries were formed based on the data collected for indicators such as economic growth, energy consumption, and CO_2 emission level. Eleven key indicators were used to identify as accurately as possible patterns in CO_2 emissions' development and formation. That is, each group's countries have similar values for the indicators that affect their emissions.

Min-max normalization was performed to reduce the excessive influence of variables with large absolute values. Noticeable, that standardized and normalized data set gave us different outcomes of clustering. Through series of experiments we found that clustering with normalized data provided more realistic clusters of the countries than the results based on the original or standardized datasets. The initial map created was thus based on a small number of random variables. This study applied the Gaussian function to determine the neighborhood of neurons for the cooperation process.

The 39 countries were, therefore, clustered according to indicators of energy consumptions, CO_2 emissions, and economic growth by constructing a Kohonen SOM using the Deductor Studio Academic software package. The vectors of 11 values were input into the map of each country's features selected during the 10-year period of 2012–2021, drawing from the data listed in Table 1. The process of creating the map necessarily included finding its optimal dimension (i.e., number of neurons). The SOM's dimension was chosen from various options based on the mean weighted quantization error criterion, which reflects the average distance between the data vectors included in the map's inputs and neuron parameters.

Results

Overall analysis

Several trial runs were conducted based on the chosen indicators of CO_2 emission levels. The results indicate that the 39-country SOM's most suitable structure is a hexagonal grid of 16 by 12 neurons. The clustering was carried out using 7,500 machine learning epochs.

Possible solutions were checked with different numbers of clusters, and the conclusion was reached that the most relevant option has eight clusters. This solution groups nations that exhibit similar decarbonization capabilities and economic growth. The 39 countries were distributed among the eight clusters numbered from 0 to 7. Each group is visually distinguishable by its shape, size, and color (the latter corresponds to a specific number on the scale at the bottom of the Kohonen map in Fig. 2).

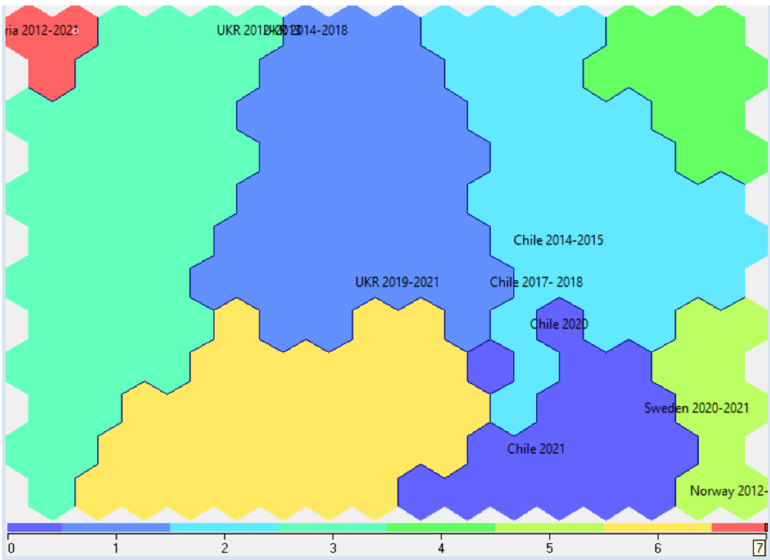

Fig. 2. Kohonen map of 8 clusters from 39 countries based on 3 subsets of indicators for 2012–2021

Table 2 offers a dynamic overview of the countries in each cluster, showing how the map helps track and analyze the nations' evolution over time. For instance, some countries (e.g., the United Kingdom, Chile, and Ukraine) changed their positions various times over the 10-year period. For example, Chile moved from Cluster 1 to 2 and then to Cluster 0, improving its CO_2 emission levels over time. This progress is indicated by Cluster 0's position closer to Cluster 5, which includes countries with the best energy, economic growth, and CO_2 emission values (i.e., ranked as low-carbon economy nations).

Table 2

CLUSTERS IN SELF-ORGANIZING MAP BASED ON 11 INDICATORS FOR 39 COUNTRIES WORLDWIDE FOR 2012–2021

Cluster 0	**Cluster 1**	**Cluster 2**	**Cluster 3**	**Cluster 4**	**Cluster 5**	**Cluster 6**	**Cluster 7**
Portugal (2012-2021) New Zealand (2012-2021) Spain (2012-2021) UK (2020) Italy (2020) Chile (2020-2021)	Argentina (2012-2020) Belgium (2012) Chile (2012-2014) Czech (2012-2021) Egypt (2012-2018) India (2020) Malaysia (2013-2021) Mexico (2012-2019) Saudi Arabia (2012-2021) Thailand (2020-2021) Turkey (2012-2015) Ukraine (2014-2021) UAE (2014-2021) UK (2012-2014)	South Africa (2012-2021) Mexico (2020-2021) Malaysia (2012, 2015-2016) Japan (2012-2021) France (2012-2021) Egypt (2014-2021) Chile (2014-2019) Canada (2012-2021) Australia (2012-2021) Argentina (2021)	Algeria (2012-2021) India (2012-2021) Indonesia (2012-2021) Kazakhstan (2012-2021) Netherland (2012-2016) Poland (2012-2021) Romania (2012-2013) Russia (2012-2021) Thailand (2012-2019) Ukraine (2012-2013) UAE (2012-2013) Uzbekistan (2012-2021)	China (2012-2021) United States (2012-2021)	Norway (2012-2021) Sweden (2012-2021)	Belgium (2012-2021) Brazil (2012-2021) Colombia (2012-2021) Germany (2012-2021) Italy (2012-2019, 2021) Netherlands (2017-2021) Romania (2014-2021) Turkey (2016-2021) UK (2015-2019, 2021)	Nigeria (2012-2021)

From 2012 to 2021, Norway and Sweden had a low level of energy intensity of GDP at consumption, oil products, natural gas and electricity consumption, with the highest renewables and wind and solar power shares in electricity. These two countries were placed in Cluster 5, in the lower right corner of the SOM (see Fig. 2 above and Fig. 3), as they are the most ecologically friendly countries of the 39 nations analyzed.

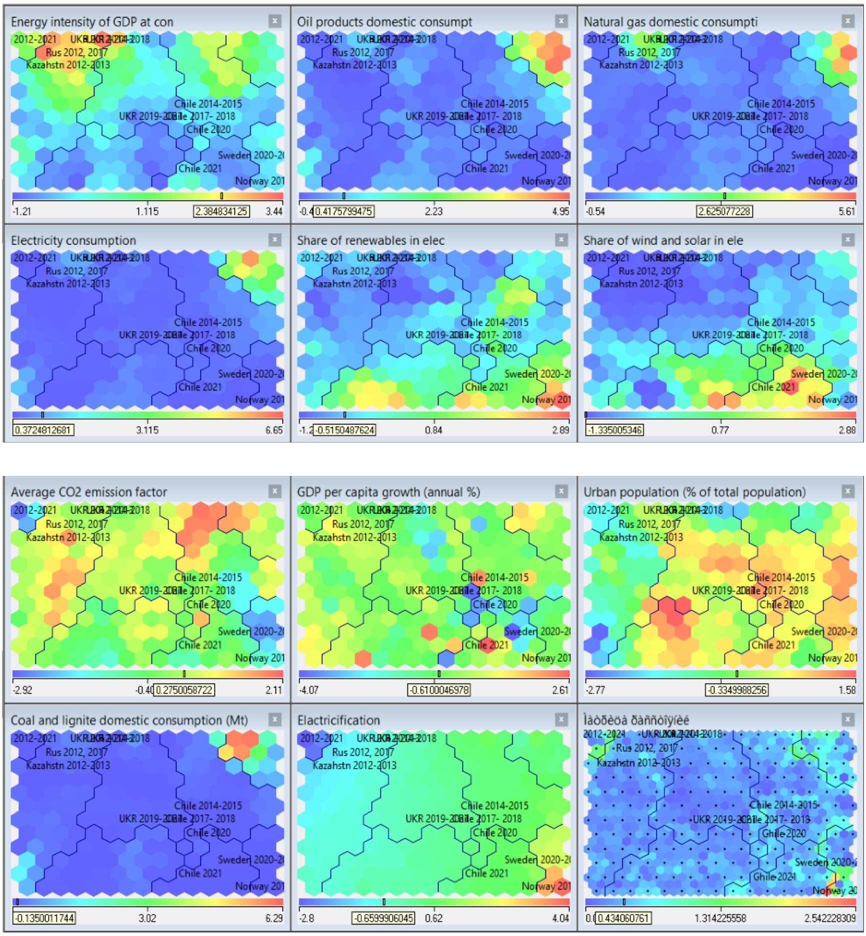

Fig. 3. Kohonen map for 39 countries based on 11 indicators for 2012–2021

Concurrently, Norway and Sweden during this 10-year period had high values for electrification, urbanization, and average growth rate in real GDP per capita, with low levels of coal and lignite domestic consumption and average CO_2 emissions (see Fig. 3 above). The results suggest that Norway and Sweden are leaders in reducing CO_2 emissions and creating climate-resilient economies.

For comparison purposes, Cluster 5 was labeled the leader cluster with the best values for the 11 indicators. All the other clusters can be seen as followers. As mentioned previously, Norway and Sweden are placed as members of Cluster 5 in the lower right corner of the map. The closer a country is to this corner of the SOM, the more highly developed is that nation's use of its decarbonization capabilities and renewable energy sources.

Notably, Cluster 7 has the worst values for all the indicators compared to the remaining clusters, and it is located opposite to the leader cluster on the map (see Fig. 2 above). Up to 2021, the countries that were quite slowly decarbonizing were Nigeria, Algeria, India, and Uzbekistan, which are located in Cluster 7 in the SOM's upper left (see Fig. 2 and Table 2 above).

The Netherlands stayed in Cluster 3 between 2012 and 2016. The results show that this country's slow progress was due to its high average CO_2 emission levels and urbanization. From 2017 onward, the Netherlands improved its position and moved closer to the leader cluster.

Some countries, such as China and the United States in Cluster 4, stayed together in the same cluster for the 10 years. They, therefore, took no steps to improve their decarbonization capabilities over the period analyzed as these countries had and continued to have extremely high CO_2 emission levels.

The SOM developed can be used to determine each nation's best position on the map. All followers may improve their energy and business sectors and identify their potential or current CO_2 emission level to draw closer to the leaders' positions. Progress entails targeting values for the 11 indicators that are closer to Cluster 5 countries' values. For example, further analysis revealed that from 2012 to 2021, Ukraine had approximately an average level of electrification, urban population, CO_2 emissions, and growth rate in real GDP per capita but relatively low levels of coal and lignite domestic consumption (see Fig. 3 above).

Trajectories of movement between clusters

This subsection focuses on Ukraine as case study to analyze its trajectory of movement from one cluster to another. This country's position was examined over the 2012–2021 period, which revealed an overall movement toward a low-carbon economy. In 2012–2013, Ukraine was in Cluster 3, then, in 2014, this nation moved to Cluster 1 and stayed there until the end of 2021 (see Table 2 above and Fig. 4). The most significant leap forward occurred in 2019, when Ukraine became the leader of Cluster 1.

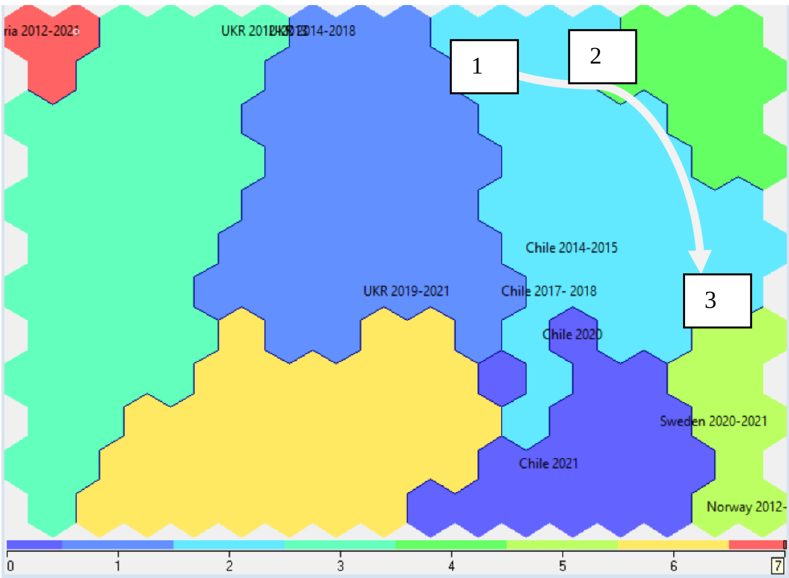

Fig. 4. Ukraine's trajectory of movement between clusters on Kohonen map for 2012–2021

Ukraine's movement between clusters from 2012 to 2021 (i.e., from point 1 to point 3 in Fig. 4 above) was in the right direction, namely, closer to Cluster 5. An analysis of international organizations and public authorities [39-41] was conducted to find an explanation for this trend. Ukraine was dealing with territorial challenges due to the Russian Federation's temporary annexation of the Autonomous Republic of Crimea and city of Sevastopol, as well as anti-terrorist operations in areas of the Donetsk and Lugansk regions in 2014 and 2015. These events dramatically changed Ukraine's development strategies [39]. Due to the conflict, it concentrated on renewable energy so that, in 2015 to 2020, renewables' share in electricity production increased from 7.9% to 11.3%) and energy consumption, GHG emissions, and pollution were significantly reduced in more recent years by applying the following financial and policy measures [40, 41]:

- In 2015, the Ministry of Ecology and Natural Resources of Ukraine developed a National Strategy on the Approximation of Ukrainian Legislation to EU Legislation for Environmental Protection.
- In 2019, the tax on GHG emissions increased four-fold, and, from 2021 onward, the government identified large and medium-sized industrial companies that had to prepare plans for monitoring GHG emissions.
- In July 2020, Ukraine officially supported the European Green Deal, designed to make the European continent climate neutral by 2050.
- In March 2021, the Cabinet of Ministers of Ukraine approved the National Economic Strategy until 2030 for achieving climate neutrality by 2060.

This country's commitment to move toward carbon neutrality implied the identification of a target CO_2 emission level, which requires an efficient, effective, and resilient economy.

The present analysis's findings can help other countries establish benchmarks for improving their own internal decarbonization activities based on other leader nations' strategies and possibly borrowing their best practices for more efficient results. Comparing one country's decarbonization capabilities (i.e., measured by the proposed 11 indicators) to those of leaders can provide hard evidence of whether that nation is competently and successfully engaging in low-carbon activities.

The proposed approach thus uses clustering to identify current and potential CO_2 emission levels to facilitate the formation of low-carbon targets at the national level. For instance, the relevant experts need to review and align Ukraine's net zero emission strategy and CO_2 emission target with the strategies implemented by EU countries in Clusters 5, 0, or 2. The results can help Ukraine to follow historical examples in order to avoid potential mistakes in the decarbonization process and more efficiently bring this nation closer to Cluster 5. Table 3 provides general suggestions for how to move Ukraine more quickly toward a cost-effective, productive low-carbon economy.

Table 3

SUGGESTIONS FOR UKRAINE BASED ON CLUSTERING RESULTS

Target clusters	Target countries (selected European Union countries from clusters to be followed)	Recommendations for how to join target clusters
Cluster 5	Norway (2012–2021) Sweden (2012–2021)	• Reduce existing domestic fossil fuel assets and, simultaneously, increase renewable energy assets by following Norway and Sweden's example. • Adjust strategies to reduce the absolute values of oil products, natural gas, coal, and lignite domestic consumption indicators. • Move toward increasing the absolute values of renewables' and wind and solar power's share in electricity consumption, as well as of electrification indicators.
Cluster 0 and Cluster 2	Portugal (2012–2021) Spain (2012–2021) France (2012–2021)	• Review current and potential CO_2 emission targets. • Align them with EU countries (i.e., Portugal, Spain, and France), thereby reducing the absolute value of average CO_2 emissions.

Countries' movement between and within clusters is characterized by changes in indicators, such as energy product consumption, and in the outcomes of policies that reduce CO_2 emissions. Nations have moved from one cluster to another by altering their status from high- to low-emission countries and vice versa. Clustering facilitates the identification of each country's level of emissions, whether high or low, for a more accurate identification of that nation's target CO_2

emission level. The proposed approach is based on using the available data on countries to place them in the most appropriate cluster. This method can be used to build a forecasting model of CO_2 emission levels for a group of nations with similar characteristics and development trends.

Conclusions

Accurately identifying target CO_2 emission levels requires appropriate effective mathematical models. This study's first research question (i.e., What are the main country clusters based on national target CO_2 emission levels?) was addressed by developing a new modelling approach to clustering nations by CO_2 emission indicators. The proposed method first segments countries according to the dynamics of a set of 11 indicators, using the Kohonen SOM toolkit. The maps generated facilitate the identification of clusters that are leaders in decarbonization and that should be followed by other countries that are passive participants in the process of lowering emissions. The present analysis's findings include conclusions drawn about the leader cluster, which contains Norway and Sweden, among other nations. The closer a country is to this cluster on the SOM, the more developed and efficient that nation's decarbonization activities are.

The second research question (i.e., How has each country's classification changed over time, with Ukraine serving as an example?) required an analysis of the map created. Ukraine improved its position over the 10 years examined by moving between clusters and drawing closer to the leader cluster. Nations in different clusters were studied to formulate recommendations to help Ukraine foster the most effective transition to low carbon emission levels.

The above results have theoretical and practical implications. The proposed method addresses past research's limitations [27-29] by classifying diverse countries and adding a temporal perspective. This research used Kohonen SOMs to define current and potential CO_2 emission levels in order help countries move in the right direction, namely, toward efficient decarbonization, which has important implications for both academics and policymakers.

Despite this study's significant contributions, the findings are limited by the availability of data for 11 selected indicators in 39 countries over the 10-year period analyzed. In addition, further research is needed to apply this Kohonen map approach at a regional and industry level.

References

1. Enerdata. (2022). *Global Energy & CO_2 Data* [Data set]. Retrieved July 1, 2022, from https://www.enerdata.net/research/energy-market-data-co2-emissions-database.html

2. Publications Office of the European Union. (2019). *A vision for the European industry until 2030: final report of the Industry 2030 high level industrial roundtable*. European Commission. https://doi.org/10.2873/102179

3. Churchill, S. A., Inekwe, J., & Ivanovski, K. (2018). Conditional convergence in per capita carbon emissions since 1900. *Applied Energy, 228*, 916-927. https://doi.org/10.1016/j.apenergy.2018.06.132

4. Cai, Y., Sam, C.Y., & Chang, T. (2018). Nexus between clean energy consumption, economic growth and CO2 emissions. *Journal of Cleaner Production, 182*, 1001–1011. https://doi.org/10.1016/j.jclepro.2018.02.035

5. Mrabet, Z., AlSamara, M., & Hezam Jarallah, S. (2017). The impact of economic development on environmental degradation in Qatar. *Environmental and Ecological Statistics, 24*(1), 7-38. https://doi.org/10.1007/s10651-016-0359-6

6. Wu, T.-H., Chen, Y.-S., Shang, W., & Wu, J.-T. (2018). Measuring energy use and CO_2 emission performances for APEC economies. *Journal of Cleaner Production, 183*, 590-601. https://doi.org/10.1016/j.jclepro.2018.02.028

7. Zhou, W.-Y, Yang, W.-L., Wan, W.-X, Zhang, J., Zhou, W., Yang, H.-S., Yang, H., Xiao, H., Deng, S.-H., Shen, F., & Wang, Y.-J. (2018). The influences of industrial gross domestic product, urbanization rate, environmental investment, and coal consumption on industrial air pollutant emission in China. *Environmental and Ecological Statistics, 25*(4), 429-442. https://doi.org/10.1007/s10651-018-0412-8

8. Li, D.-C., Chang, C.-J., Chen, C.-C., & Chen, W.-C. (2012). Forecasting short-term electricity consumption using the adaptive grey-based approach — an Asian case. *Omega, 40*(6), 767–773. https://doi.org/10.1016/j.omega.2011.07.007

9. Schandl, H., Hatfield-Dodds, S., Wiedmann, T., Geschke, A., Cai, Y., West, J., Newth, D., Baynes, T., Lenzen, M., & Owen, A. (2016). Decoupling global environmental pressure and economic growth: scenarios

for energy use, materials use and carbon emissions. *Journal of Cleaner Production*, *132*, 45-56. https://doi.org/10.1016/j.jclepro.2015.06.100

10. Al-mulali, U., Weng-Wai, C., Sheau-Ting, L., & Mohammed, A. H. (2015). Investigating the environmental Kuznets curve (EKC) hypothesis by utilizing the ecological footprint as an indicator of environmental degradation. *Ecological Indicators*, *48*, 315–323. https://doi.org/10.1016/j.ecolind.2014.08.029

11. He, Z., Xu, S, Shen, W., Long, R., & Chen, H. (2017). Impact of urbanization on energy related CO_2 emission at different development levels: regional difference in China based on panel estimation. *Journal of Cleaner Production*, *140*(3), 1719-1730. https://doi.org/10.1016/j.jclepro.2016.08.155

12. Li, T., Wang, Y., & Zhao, D. (2016). Environmental Kuznets curve in China: New evidence from dynamic panel analysis. *Energy Policy*, *91*, 138–147. https://doi.org/10.1016/j.enpol.2016.01.002

13. Zi, C., Jie, W., & Hong-Bo, C. (2016). CO_2 emissions and urbanization correlation in China based on threshold analysis. *Ecological Indicators*, *61*(2), 193-201. https://doi.org/10.1016/j.ecolind.2015.09.013

14. Appiah, K., Du, J., & Poku, J. (2018). Causal relationship between agricultural production and carbon dioxide emissions in selected emerging economies. *Environmental Science and Pollution Research*, *25*, 24764-24777. https://doi.org/10.1007/s11356-018-2523-z

15. Sarkodie, S. A., & Owusu, P. A. (2017). The relationship between carbon dioxide, crop and food production index in Ghana: By estimating the long-run elasticities and variance decomposition. *Environmental Engineering Research*, *22*(2), 193-202. https://doi.org/10.4491/eer.2016.135

16. Appiah, K., Du, J., Yeboah, M., & Appiah, R. (2019). Causal Correlation between Energy Use and Carbon Emissions in Selected Emerging Economies—Panel Model Approach. *Environmental Science and Pollution Research*, *26*, 7896-7912. https://doi.org/10.1007/s11356-019-04140-2

17. Apergis, N., & Payne, J. E. (2012). Renewable and Non-renewable Energy Consumption-Growth Nexus: Evidence from a Panel Error Correction Model. *Energy Economics*, *34*(3), 733-738. https://doi.org/10.1016/j.eneco.2011.04.007

18. Dogan, E., & Seker, F. (2016). Determinants of CO_2 Emissions in the European Union: The Role of Renewable and Non-renewable Energy. *Renewable Energy*, *94*, 429-439. https://doi.org/10.1016/j.renene.2016.03.078

19. Asafu-Adjaye, J., Byrne, D., & Alvarez, M. (2016). Economic Growth, Fossil Fuel and Non-fossil Consumption: A Pooled Mean Group Analysis Using Proxies for Capital. *Energy Economics*, *60*, 345-356. https://doi.org/10.1016/j.eneco.2016.10.016

20. Boamah, K. B., Du, J., Boamah, A. J., & Appiah, K. (2018). A Study on the Causal Effect of Urban Population Growth and International Trade on Environmental Pollution: Evidence from China. *Environmental Science and Pollution Research, 25*, 5862-5874. https://doi.org/10.1007/s11356-017-0882-5

21. Kim, D.-H., Suen, Y.-B., & Lin, S.-C. (2019). Carbon Dioxide Emissions and Trade: Evidence from Disaggregate Trade Data. *Energy Economics, 78*, 13-28. https://doi.org/10.1016/j.eneco.2018.08.019

22. Xu, R, & Wunsch, D. (2005). Survey of Clustering Algorithms. *IEEE Transaction on Neural Network*, *16*(3), 645-678. https://doi.org/10.1109/TNN.2005.845141

23. Harkanth, S., & Phulpagar, B. D. (2013). A survey on clustering methods and algorithms. *International Journal of Computer Science and Information Technologies, 4*(5), 687-691. https://ijcsit.com/docs/Volume%204/Vol4Issue5/ijcsit2013040511.pdf

24. Bini, B. S., & Mathew, T. (2016). Clustering and Regression Techniques for Stock Prediction. *Procedia Technology, 24*, 1248–1255. https://doi.org/10.1016/j.protcy.2016.05.104

25. Lukianenko, D., & Strelchenko, I. (2021). Neuromodeling of features of crisis contagion on financial markets between countries with different levels of economic development. *Neiro-Nechitki Tekhnolohii Modelyuvannya v Ekonomitsi (Neuro-Fuzzy Modeling Techniques in Economics), 10*, 136-163. http://doi.org/10.33111/nfmte.2021.136

26. Velykoivanenko, H., & Korchynskyi, V. (2022). Application of Clustering in the Dimensionality Reduction Algorithms for Separation of Financial Status of Commercial Banks in Ukraine. *Universal Journal of Accounting and Finance*, *10*(1), 148-160. http://doi.org/10.13189/ujaf.2022.100116

27. Gong, B., Zheng, X., Guo, Q., & Ordieres-Meré, J. (2019). Discovering the patterns of energy consumption, GDP, and CO_2 emissions in China using the cluster method. *Energy*, *166*, 1149-1167. https://doi.org/10.1016/j.energy.2018.10.143

28. Csereklyei, Z., Anantharama, N., & Kallies, A. (2021). Electricity market transitions in Australia: Evidence using model-based clustering. *Energy Economics*, *103*, Article 105590. https://doi.org/10.1016/j.eneco.2021.105590

29. Inekwe, J., Maharaj, E. A. & Bhattacharya, M. (2020). Drivers of carbon dioxide emissions: an empirical investigation using hierarchical and non-hierarchical clustering methods. *Environmental and Ecological Statistics*, *27*, 1–40. https://doi.org/10.1007/s10651-019-00433-4

30. The World Bank. (2022). *World Development Indicators* [Data set]. Retrieved July 1, 2022, from https://datacatalog.worldbank.org/search/dataset/0037712

31. United Nations Statistics Division. (2022). *UNdata* [Data set]. Retrieved July 1, 2022, from http://data.un.org/Explorer.aspx

32. United Nations Climate Change. (2022). *Time Series* - *Annex I* [Data set]. Retrieved July 1, 2022, from https://di.unfccc.int/time_series

33. International Renewable Energy Agency. (2022). *Statistics Data* [Data set]. Retrieved July 1, 2022, from https://irena.org/Statistics

34. Eurostat. (2022). *DATABASE* [Data set]. Retrieved July 1, 2022, from https://ec.europa.eu/eurostat/en/web/main/data/database

35. Enerdata. (2022). *World Energy & Climate Statistics – Yearbook 2022* [Data set]. Retrieved July 1, 2022, from https://yearbook.enerdata.net/total-energy/world-consumption-statistics.html

36. Kohonen, T. (2001). *Springer Series in Information Sciences: Vol. 30. Self-organizing maps* (3rd ed.). Springer. https://doi.org/10.1007/978-3-642-56927-2

37. Wehrens, R., & Kruisselbrink, J. (2018). Flexible Self-Organizing Maps in kohonen 3.0. *Journal of Statistical Software*, *87*(7), 1-18. https://doi.org/10.18637/jss.v087.i07

38. Matviychuk, A., Lukianenko, O., & Miroshnychenko, I. (2019). Neuro-fuzzy model of country's investment potential assessment. *Fuzzy economic review*, *24*(2), 65-88. https://doi.org/10.25102/fer.2019.02.04

39. Food and Agriculture Organization of the United Nations. (2020). *Intended Nationally Determined Contribution (INDC) of Ukraine to a New Global Climate Agreement*. https://www.fao.org/faolex/results/details/en/c/LEX-FAOC190395/

40. UNICEF. (2021). *Climate Landscape Analysis for Children (CLAC) in Ukraine*. https://www.unicef.org/ukraine/media/15766/file/Climate%20Landscape%20Analysis%20for%20Children%20(CLAC)%20in%20Ukraine.pdf

41. Ministry of Ecology and Natural Resources of Ukraine. (2021). *Analytical review of the updated nationally determined contribution of Ukraine to the Paris agreement*. https://mepr.gov.ua/files/docs/klimatychna_polityka/Analytical%20Review%20Updated%20Nationally%20Determined%20Contribution%20of%20Ukraine%20to%20the%20Paris%20Agreement%20July%202021%20(2).pdf

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INTELLECTUAL CAPITAL MANAGEMENT OF THE BUSINESS COMMUNITY BASED ON THE NEURO-FUZZY HYBRID SYSTEM

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The modern economy needs to address the issue of assessing intellectual capital as the basis for the development of market relations. The search for ways to solve this problem is possible based on the use of soft methods. The aim of the article is to develop a structural model for managing the intellectual capital of the business community based on an appropriate neuro-fuzzy system. Developed on the basis of soft computing methods, an innovative model for estimating intellectual capital of the business community is able to process "non-rigorous", incomplete or distorted input data, work with qualitative concepts, ambiguous and uncertain statements, perform operations with weak formalized economic parameters. The experimental results obtained made it possible to formulate the methods for evaluating the intellectual capital of business communities (or other similar economic systems) characterized by fuzzy relations between input and output parameters, considerable difficulties in formalizing the factors of influence, capability of using linguistic experts' statements for building an information and analytical system, etc. The developed hybrid neuro-fuzzy system “Board” for evaluating intellectual capital of a business community enables to process both quantitative and qualitative input data, and was built up according to the criteria of digital economy transformation projects.

Keywords: *intellectual capital, management, modeling, fuzzy logic, business community*

JEL Classification: C45, M12, O34

Introduction

Modern economic development is characterized by fundamental changes in the technological basis of societal manufacturing and shift to innovative economics. Special role in this process belongs to the intellectual capital largely defining the structure of the domestic economy, the quality of manufactured goods and services, as well as the efficiency of economic functioning on all organizational levels. The development of the intellectual labour and its proportion in the production processes are becoming the most important factors defining the integration of a country in the world economy, its export capabilities and share in the total world monetary income.

In developed countries, the improvement of scientific technological progress, intellectual and innovative technological production are in the center of attention. According to estimations [1], the share of new technologies in developed countries makes up 85% of the GDP growth, and in the 15-25 the share of digital economy will be 50% of the world GDP. Thanks to highly technological and science capacious goods, these countries are at an advantage in the world economy and labour market, especially under conditions of globalization and digitalization of economic systems.

The current stage of technological development, economy and education calls for tackling the issue of intellectual capital management based on modern mathematical methods. The topicality of the research is determined by the processes of digital transformation in economy, which differ from the previous automatization and informatization periods by the large-scale transformation of business models, structural organizations and interrelation of economic agents. These processes result in emergence of new digital products, forms of economic organization – digital platforms and ecosystems.

Therefore, nowadays the issue of intellectual capital management in the conditions of digitalization acquires a new meaning in terms of forming effective administrative economic mechanisms of accumulating and increasing intellectual capital of both modern enterprises and business communities.

The issue "intellectual capital" (IC) has certain stages of its development. Bontis, N., director of the Institute for Intellectual Capital Research, in his article [2] indicates that the concept of intellectual capital was first introduced by economist Galbraith, J. [3] in 1967. One of the first works that laid the foundation for independent research on intellectual capital was the book of the Japanese scientist Sakaiya, T. "The value created by knowledge, or the history of the future" [4]. He concludes that knowledge is directly embodied in the majority of created goods and, thus, the economy turns into a system that functions on the basis of the exchange of knowledge and their mutual assessment.

Synthesizing the concepts studied by Petty, R. and Guthrie, J. [5], one can single out the main origins of the theory of the intellectual capital from 1980 to 2000. In particular, a certain dependence of the practice on the fundamentals of the intellectual capital is noted.

In 1997, Edvinsson, L. and Malone, M. published their first book "Intellectual capital" which was a pioneer in this sphere [6]. It reflects the experience of defining, evaluating and managing intellectual capital of a Swedish corporation "Skandia", which was the first to publish in its report the information on intellectual capital.

In the conditions of digitalization of economies, the most relevant is the definition of intellectual capital, proposed by Bontis, N. [2], who regards it from the point of stability of economic development [7].

Nowadays, there are dozens of methods of intellectual capital assessment [8]. Tobin's coefficient q [9] (or Kaldor's rate [10]) can refer to the classical intellectual capital evaluation methods – it is the ratio of the company's market value to the price of its tangible assets substitution (buildings, houses, equipment and stock). To evaluate intangible assets EVA (Economic Value-Added) methods are used [11]. Back in 1989, Finegan, P. proposed the concept of EVA [12], but it gained popularity only in 1993 with the publication of an article by Tully, S. and Hadjian, A. in “Fortune” journal [13]. This method regards humans rather as assets than value. Although this methods is effective for evaluating intangible assets, it does not answer the question how these values are created and developed.

Another group of popular methods is based on considering various values of intellectual capital to develop the evaluation indicators. As a variant of such an assessment is a popular method Navigator made up by a Swedish insurance company “Skandia”, which has practiced in evaluating intellectual capital since 1994. Here we can single out several categories of intellectual capital: human capital, structural capital, relations capital (market capital) [14]. The most common form of the intellectual capital is intellectual property, comprising trade marks, patents, licenses, etc.

Another example of this group is the method of Intangible Assets Monitor (Sveiby, K.-E. et al. [15]), which divides intangible assets into external and internal structures and employees’ competency. The choice of evaluation indicators depends on strategic goals. The most important spheres of applying this method are growth/renovation, efficiency and stability. Many companies develop their indicators by this method.

A separate group of methods presents the so called “third generation” of intellectual capital indicators. While characterizing employee’s proficiency, they also take into account their activity coefficient (for instance, the number of days of training), as well as transforming activity (comprehension of better practice through implicit human knowledge). These methods include the IC Index [16] – identification of four main categories of intellectual capital (relations, employees, infrastructure, innovations) and their representation in the hierarchy. IC Rating [17] also relates to this group of methods, and presents a hierarchical structure supplied with a risk factor. The most peculiar feature of these methods is that they enable the managers not only to register value constituents, but also consider some trends and factors lying at the basis of the situation, including risk sensitive ones.

The issue if evaluation and management of intellectual capital was also considered in Project Management methods. They started their development in the 1950s in decision theory and operations research in the works of Malcolm, D. et al. [18] (Program Evaluation and Review Technique, PERT), Magee, J. [19] (Decision Tree Analysis, DTA), Kelley, J. et al. [20] (Critical Path Method, CPM), Goldratt, E. [21] (Critical Chain Method, CCM), Fleming, Q. and Koppelman, J. [22] (Earned Value Technique, EVT) and others. Thus, it enables to state that all the methods of intellectual capital management have one common problem of incapability of simultaneous consideration of qualitative and quantitative factors. However, this problem can be solved by fuzzy calculations methods [23, 24].

The specificity of project management, in particular, is studied in the works of Turner, R. [25], Antoniuk, L. et al. [26], Zavidna, L. et al. [27], including with the use of fuzzy mathematics tools in the papers by Balan, V. [28] and authors of this article [29].

The aim and tasks of the research

The aim of the article is to develop a structural model for managing the intellectual capital of the business community based on an appropriate neuro-fuzzy system. This model will consider incomplete or subjective quantitative or qualitative information, which will enable to obtain verbalized results of evaluating the intellectual capital of business community.

Results

The study “Small Business Index” [30] proved that businesses acting within any business community are more successful. Such businesses have positive feedbacks, steady dynamics of clients’ and sales growth, thus income growth. These companies have a better access to necessary resources, technologies and investments.

The research [31] shows that business community represents different sectors of large, small and middle entrepreneurship, and protects their rights and legal business interests, supports effective communication among them and state administrative bodies on creating favourable business conditions in Ukraine and abroad, provides access to innovative technologies, counselling and other professional non-income services. The aim of business community is to create and spread innovative knowledge and technologies in business, establishing relations among the economic agents for their better mutual profiting.

The problem of assessing the intellectual capital of business communities is new in modern science. We provide evaluation of intellectual capital on the example of a business community "Board" [32], which is typical for this class of economic agents. "Board" is a business community that provides mutual mentoring and counseling for prompt and effective business decision making of each member. In June 2022 "Board" counted over 1000 members, including 982 Ukrainian and 130 foreign ones.

To evaluate intellectual capital of a business community "Board" by the principles of fuzzy logic [23, 24, 33, 34], we propose an approach (see Fig. 1), within which the corresponding neuro-fuzzy hybrid system (NFHS) is implemented.

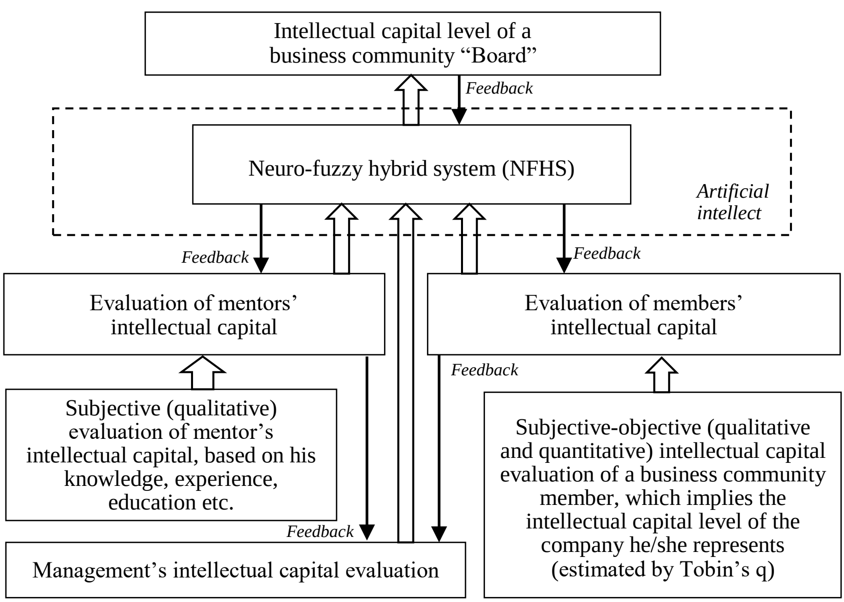

Fig. 1. Hybrid system for evaluating the intellectual capital of the business community

The methods of developing hybrid intellectual systems are based on problem-structured and problem-instrumental methodology, which consists in analysis and decomposition of a complex problem with further synthesis of solutions into structures or program components for the set subproblems. At the basis of these systems suffice it to use "soft" calculations able to process "non-rigorous", incomplete or distorted input data, work with qualitative concepts, ambiguous and vague statements, loosely formalized economic parameters.

To realize the neuro-fuzzy hybrid system in accordance with the approach presented in Fig. 1, the following factors must be determined:

– evaluation of mentors' intellectual capital on the basis of his/her knowledge, education, competencies and experience, defined by the management of business community "Board" on the basis of linguistic qualitative estimation;

– evaluation of the intellectual capital of a business community member, which implies subjective-objective estimation of company's intellectual capital, calculated by Tobin's q, i.e. relation of company's market value to the price of its assets substitution;

– intellectual capital evaluation of community's managers/founders ("Board") on the basis of subjective neurolinguistic estimation of mentors and members of companies. It should be noted that NFHS will have no feedback with this evaluation function to prevent the system collapse, i.e. conflict of estimation values.

The NFHS will be developed basing on the thesis, that the main principle of flexible project management of digital transformation is the process of predictive recognition of problem situations and group work on measures considering the interests of stakeholders (all members of business community). Formalization of this process is realized by the presence of feedback, which implements problem-predictive management (see Fig. 1).

In June 2022, when the NFHS was being developed, the general number of business community "Board" members and mentors makes up 1000 persons (these data will be used as a basis for modeling).

To assess the intellectual capital of the business community, the following variables of NFHS were defined:

– $S_{1\ldots n}$ – subjective evaluation of the intellectual capital of the mentors of the business community “Board” (the scale from 0 to 100 points), which is formed basing on the opinions of the business community managers (where *n* is the mentors number);

– $T_{1\ldots h}$ – subjective-objective evaluation of the intellectual capital of the companies with the membership in the business community “Board”, calculated by Tobin’s q and presented by the members of business community (*h* is the number of companies);

– $K_{1\ldots 3}$ – subjective-objective evaluations of the intellectual capital of three founders of the business community “Board” based on survey of expert estimations of mentors and members. To simplify the calculations, the general integral estimation of the founders of the business community “Board” will be done. At the moment of starting gathering information, the level of the managers’/founders’ intellectual capital made up 93 points by a 100-point scale.

In line with methodological approaches to development of neuro-fuzzy systems [23, 24, 33-38], we will build NFHS for evaluating the intellectual capital of the business community “Board” in the form of an “inference tree” (see Fig. 2). It has the following designations: *M* – integral evaluation of the mentors’ intellectual capital; *U* – integral evaluation of the members’ intellectual capital; *K* – integral evaluation of the intellectual capital of the business community managers/founders; *IKB* – integral evaluation of the intellectual capital of the business community “Board”.

The nods of the “inference tree” are interpreted in the following way: the root f_{IKB} corresponds to the level of the intellectual capital of business community “Board”; terminal nods are the corresponding factors of influence; non-terminal nods (double circles) represent integral indicators calculated on the basis of the partial influence factors that they include. All nodes of the “inference tree” are described by linguistic variables.

For the description of the quantitative input parameters $\{T_1 \ldots T_h\}$ we used the calculations, performed by the members of the business community “Board”; for the description of the qualitative parameters *S*, *M*, *U*, *K* and *IKB*, scores on a 100-point scale were used.

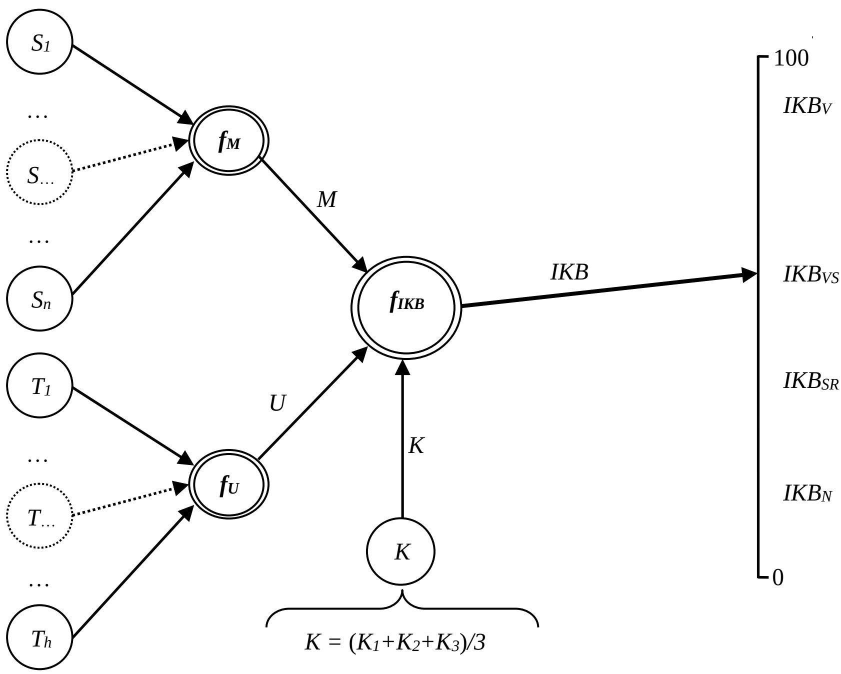

Fig. 2. Structure of the NFHS evaluation of the intellectual capital of the business community "Board"

The neurolinguistic evaluation with the corresponding scale of changes for the input factors and output indicator is demonstrated in Table 1. Table 1 also shows the values of the parameters of the bell-shaped membership functions of all variables according to [39, 40]:

$$\mu^{T}(x) = \frac{1}{1+\left[\dfrac{x-b}{c}\right]^{2}}, \tag{1}$$

where b and c are the parameters of bell-shaped membership function: b – coordinate of function maximum; c – coefficient of stretching/ concentration.

The choice of membership function of bell-shaped type (1) is predetermined by its simplicity and flexibility, since it has only two parameters and simple derivative, which makes it more convenient for further NFHS tuning.

Table 1

VARIABLES OF NFHS FOR EVALUATING THE INTELLECTUAL CAPITAL OF THE BUSINESS COMMUNITY "BOARD"

Factor	Symbol	Range of changes	Linguistic estimation (term), value range	Values of *b* and *c* of membership function (1)	
				b	*c*
Mentors' IC estimation	$S_1 \ldots S_n$	0…100	Low (*N*), 0…50 Medium (*Sr*), 50…75 High (*V*), 75…100	25 65 85	30 40 20
Members' IC estimation	$T_1 \ldots T_h$	0…3	Low (*N*), 0…0.5 Medium (*Sr*), 0.5…1.2 High (*V*), 1.2…3	0.4 0.9 1.8	1 1.2 1.4
Integral estimation of IC of managers of the business community	*K*	0…100	Low (*N*), 0…50 Medium (*Sr*), 50…75 High (*V*), 75…100	25 67 82	33 37 25
Integral estimation of mentors' IC	*M*	0…100	Low (*N*), 0…50 Medium (*Sr*), 50…75 High (*V*), 75…100	20 63 85	30 40 15
Integral estimation of members' IC	*U*	0…100	Low (*N*), 0…50 Medium (*Sr*), 50…75 High (*V*), 75…100	27 60 82	35 40 25
Integral estimation of IC of the business community "Board"	*IKB*	0…100	Low (*N*), 0…40 Medium (*SR*), 40…60 Higher than medium (*VS*), 60…80 High (*V*), 80…100	20 50 70 90	25 20 25 15

The presented in Fig. 2 connections can be described in the following functions in general form:

$$M = f_M(S_1 \ldots S_n); \quad (2)$$

$$U = f_U(T_1 \ldots T_h); \quad (3)$$

$$K = (K_1+K_2+K_3)/3, \quad (4)$$

where $K_{1\ldots3}$ are the subjective-objective evaluations of the intellectual capital of the three founders of the business community "Board" based on expert estimations of mentors and members. The founders who manage this business are evaluated by both members and mentors on the basis of a closed survey. The points obtained are reduced to the arithmetic mean first for each founder, and then the total score K averaging over them (4).

The value of the output indicator IKB, i.e. the level of IC of the business community "Board", can be given in the formula:

$$IKB = f_{IKB}(M, U, K). \quad (5)$$

Using experts' recommendations [32] and basing on the certain economic situation, the intellectual capital of the business community "Board" can be characterized according to the following levels on a 100-point scale:

- IKB_V (80-100] – high IC (class A);
- IKB_{VS} (60-80] – IC higher than medium/average (class B);
- IKB_{SR} (40-60] – medium IC (class C);
- IKB_N [0-40] – low IC (class D).

The next stage of building NFHS of evaluating IC of the business community "Board" is building the membership functions for all factors and the output indicator. The membership functions are descriptive ones, which define the range of change in the values of variables (input and output) by terms (linguistic estimations of indicators, which are proper names for the corresponding fuzzy sets). For instance, Fig. 3 demonstrates the membership functions for all linguistics terms of the output indicator (the levels of intellectual capital of the business community "Board").

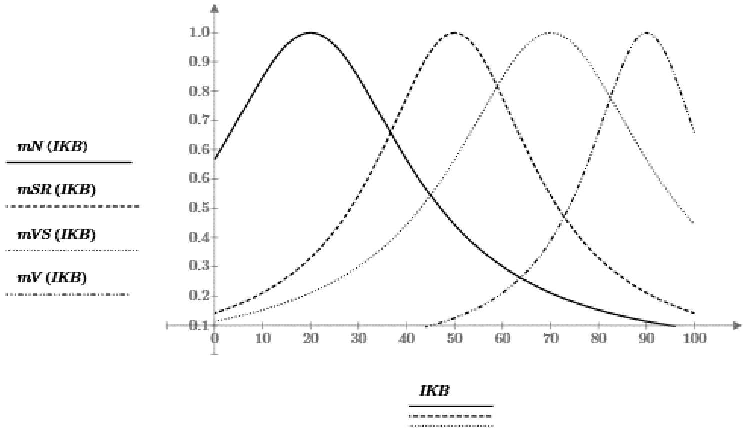

Fig. 3. Membership functions for the output indicator (intellectual capital levels of the business commuity "Board")

To form the final equation of NFHS on evaluating the intellectual capital of the business community "Board" by neurolinguistic modeling methods, in addition to describing the influencing factors, it is necessary to define the dependencies and the impact of these factors on the output indicator. For this purpose, on the basis of expert data, hierarchical knowledge bases were developed that implement dependencies in formulas (2), (3), (5). These dependences are "If-Then" rules [23, 24, 33-40]. Partial examples of these hierarchical knowledge bases are given in Tables 2-4.

Table 2

A SEGMENT OF KNOWLEDGE BASE FOR EVALUATING THE MENTORS' IC OF THE BUSINESS COMMUNITY "BOARD"

S_1	S_2	S_3	…	S_n	M	w
N	*N*	*N*	…	*Sr*	*N*	w_1
Sr	*N*	*Sr*	…	*N*	*N*	w_2
Sr	*Sr*	*Sr*	…	*N*	*Sr*	w_3
Sr	*V*	*N*	…	*N*	*Sr*	w_4
…	…	…	…	…	…	…
V	*V*	*V*	…	*V*	*V*	w_{49}
V	*V*	*Sr*	…	*V*	*V*	w_{50}

Table 3

A SEGMENT OF KNOWLEDGE BASE FOR EVALUATING THE MEMBERS' IC OF THE BUSINESS COMMUNITY "BOARD"

T_1	T_2	T_3	…	T_h	U	w
N	*N*	*N*	…	*Sr*	*N*	w_{51}
Sr	*N*	*Sr*	…	*N*	*N*	w_{52}
Sr	*Sr*	*Sr*	…	*N*	*Sr*	w_{53}
Sr	*V*	*N*	…	*N*	*Sr*	w_{54}
…	…	…	…	…	…	…
V	*V*	*V*	…	*V*	*V*	w_{999}
Sr	*V*	*Sr*	…	*V*	*V*	w_{1050}

As mentioned above, the evaluation of the intellectual capital of management/founders of the business community "Board" is performed on the basis of expert evaluations of surveyed mentors and members. Value K is equal to the average value of mentors' and members' assessments on a scale from 0 to 100 points. As for March-April 2022, the integral level of IC of managers/founders made up 93 points.

The knowledge base of the final equation of NFHS for evaluating the intellectual capital of the business community "Board" is presented in Table 4.

Table 4

KNOWLEDGE BASE FOR EVALUATING THE INTELLECTUAL CAPITAL OF THE BUSINESS COMMUNITY "BOARD"

M	*U*	*K*	*IKB*	w
N	*N*	*N*	*N*	w_{1051}
N	*Sr*	*N*	*N*	w_{1052}
Sr	*N*	*N*	*N*	w_{1053}
Sr	*Sr*	*Sr*	*SR*	w_{1054}
N	*V*	*Sr*	*SR*	w_{1055}
V	*Sr*	*N*	*SR*	w_{1056}
Sr	*Sr*	*V*	*VS*	w_{1057}
V	*Sr*	*Sr*	*VS*	w_{1058}
Sr	*V*	*Sr*	*VS*	w_{1059}
V	*V*	*V*	*V*	w_{1060}
V	*V*	*Sr*	*V*	w_{1061}
Sr	*V*	*V*	*V*	w_{1062}

Operations with these knowledge bases, presented in Tables 2-4, are performed in the mathematic package Matlab [41]. In each rule, the membership functions of the input factors to the terms specified in the rule are integrated using the logical operator "And" (implemented by operations of multiplication or minimum) and multiplied by the weight of the rule *w* (in the range from 0 to 1). These weights and the parameters of all membership functions are used to tune the model. The results of calculations of all rules related to one term of the output variable are combined through the logical operator "Or" (summation or maximum operations). So, the linguistic expressions presented in Table 4 correspond to the following fuzzy logic equations:

$$
\begin{aligned}
\mu^{N}(IKB) &= w_{1051} \cdot [\mu^{N}(M) \cdot \mu^{N}(U) \cdot \mu^{N}(K)] \vee \\
&\vee w_{1052} \cdot [\mu^{N}(M) \cdot \mu^{Sr}(U) \cdot \mu^{N}(K)] \vee \\
&\vee w_{1053} \cdot [\mu^{Sr}(M) \cdot \mu^{N}(U) \cdot \mu^{N}(K)]; \\
\mu^{SR}(IKB) &= w_{1054} \cdot [\mu^{Sr}(M) \cdot \mu^{Sr}(U) \cdot \mu^{Sr}(K)] \vee \\
&\vee w_{1055} \cdot [\mu^{N}(M) \cdot \mu^{V}(U) \cdot \mu^{Sr}(K)] \vee \\
&\vee w_{1056} \cdot [\mu^{V}(M) \cdot \mu^{Sr}(U) \cdot \mu^{N}(K)]; \\
\mu^{VS}(IKB) &= w_{1057} \cdot [\mu^{Sr}(M) \cdot \mu^{Sr}(U) \cdot \mu^{V}(K)] \vee \\
&\vee w_{1058} \cdot [\mu^{V}(M) \cdot \mu^{Sr}(U) \cdot \mu^{Sr}(K)] \vee \\
&\vee w_{1059} \cdot [\mu^{Sr}(M) \cdot \mu^{V}(U) \cdot \mu^{Sr}(K)]; \\
\mu^{V}(IKB) &= w_{1060} \cdot [\mu^{V}(M) \cdot \mu^{V}(U) \cdot \mu^{V}(K)] \vee \\
&\vee w_{1061} \cdot [\mu^{V}(M) \cdot \mu^{V}(U) \cdot \mu^{Sr}(K)] \vee \\
&\vee w_{1062} \cdot [\mu^{Sr}(M) \cdot \mu^{V}(U) \cdot \mu^{V}(K)].
\end{aligned} \tag{6}
$$

The values of membership functions in the equations (6) are defined by the knowledge bases characterizing the IC of mentors, members and founders/managers of the business community "Board". Fuzzy logic equations (6) are mathematic implementation of NFHS of IC evaluation of the business community "Board".

The defuzzification procedure is the last stage of NFHS development and is a reverse transformation of the received fuzzy estimate into the exact value of the output variable. There are various defuzzification methods, the choice and application of which depends on the object of modeling [35, 40].

Due to the peculiarities of NFHS and the output variable, to calculate its exact value, we will choose the defuzzification method, named “centrifugation method extended” [35]:

$$IKB = \frac{\sum_{i=1}^{n} \left[IKB_{min} + (i-1) \cdot \frac{IKB_{max} - IKB_{min}}{n-1} \right] \cdot \mu_i}{\sum_{i=1}^{n} \mu_i}, \qquad (7)$$

where n is the number of terms of the variable IKB (in our case $n = 4$); IKB_{min}, IKB_{max} are the measurement scale range; μ_i is a membership function value.

Defuzzification procedure provides the final result of the evaluation of the business community “Board” intellectual capital based on the constructed NFHS.

In the mathematic package Matlab 6.1, an experiment was carried out using above mentioned method (developed NFHS). Calculations for evaluation of IC of the business community “Board” amounted to 82 points. According to the obtained results of NFHS calculations on the evaluating IC of the business community “Board”, we can state that it refers to a “high IC” class A (obtained 82 points out of 100).

Based on the results obtained, it is possible to formulate the method of evaluation of the intellectual capital of the business community (or/and other economic systems) through the following stages:

– step 1: state the values of influence factors $S_{1 \ldots n}$, $T_{1 \ldots h}$, $K_{1 \ldots 3}$;

– step 2: find the membership levels of influencing factors $S_{1 \ldots n}$, $T_{1 \ldots h}$, $K_{1 \ldots 3}$, K, M, U, corresponding to the linguistic terms by formula (1). The values of the parameters b and c of the membership functions are presented in Table 1;

– step 3: develop the expert knowledge bases for calculating the integral variables M, U and IKB of the NFHS;

– step 4: calculate the integral estimation K of IC of the managers of the business community according to the formula (4);

– step 5: on the basis of the obtained knowledge bases, make calculations to find the output value of NFHS;

– step 6: to carry out defuzzification procedure (7) and find the quantitative output value;

– step 7: when necessary to perform optimization procedure for the NFHS.

The proposed cognitive approach to developing NFHS is an effective instrument for modeling and visualizing managerial decisions on the development of complex economic systems (for instance, evaluation of the intellectual capital) through integration of quantitative factor analysis and expert evaluation of qualitative indicators and systemic relations between them. The potential of the cognitive approach to solving economic problems is determined by infeasibility of some methods of economic forecasting and extrapolation in conditions of complex, instable, irregular or crisis economic situation [42]. The standard methods are meant for defining steady trends, therefore any available transition processes can distort modeling results.

The developed NFHS of evaluating IC of the business community "Board" can be regarded as a typical one for the given class of objects. The methods proposed in its construction can be applied for evaluation of other economic processes characterized by fuzzy relations between input and output parameters, significant difficulties at formalization of influence factors, possibility to use experts' linguistic expressions for building a system, etc.

On the basis of the obtained results we will develop an economic mechanism of managing the IC of the business community "Board" in conditions of digitalization, which will refer to the category of "flexible management models" (see Fig. 4).

The mechanism of managing the intellectual capital of the business community "Board" is based on the fact that the management of business community evaluates and elects mentors as the main IC bearers. These have to pass their knowledge and skills to other members of business community. The manager-mentor relationship is of utmost importance for the success of the business community, especially in a highly competitive environment. While endorsing decisions on evaluating IC of managers and mentors of the business community "Board", it is also important to take into consideration differences of opinion between experts (mentors), because these have restricted rationality, which does not concern their proficiency.

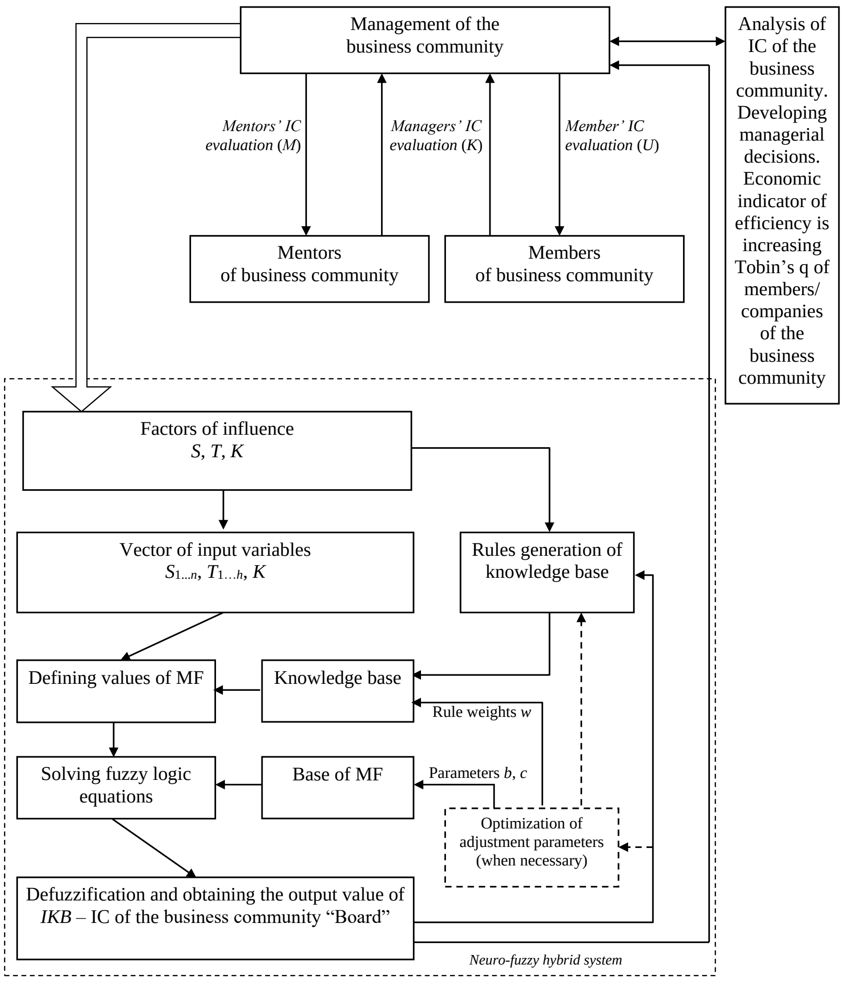

Fig. 4. IC management of the business community "Board"

The relation manager-member in this model is of lesser value, since the main task of business community is to spread innovative knowledge and technologies. Therefore, a member can have any IC, but must aspire to increase and capitalize it in his own business (although in certain conditions, the management of business community can influence it indirectly, not accepting candidates with a low IC as a member). The member's IC level is calculated by his Tobin's q, which is the most economical factor in the system. The aim of business community is to increase the member's Tobin's q incorporating knowledge technologies. In their activity, the management of the business community monitors a member's Tobin's q. If it shows growth, it testifies the rise of the intellectual capital of the whole business community.

Thus, it is a simultaneous aim of both a member and the management, while the mentor acts as a means of achieving it. It is on the basis of the NFHS, does the management of the business community makes corresponding managerial decisions, mainly involving mentors with certain competencies and knowledge, who can influence the performance of other members of the business community. Thus, there is a bilateral connection between the management, mentors and members of the business community in the system of general IC evaluation, as seen from Fig. 4. But it should be noted once again that the main element in the management decision-making system is the business community's management.

Conclusions and prospects of further research

Cognitive approach [43] on the basis of neuro-fuzzy methodology is an effective mechanism of modeling the managerial decisions for the development of complex economic systems, to which we refer the process of managing the intellectual capital of business communities due to integration of the analysis of quantitative factors and expert evaluations of system relations among them. The perspectivity of applying the cognitive approach to solving economic problems (not only IC evaluation and management) is explained by infeasibility of some methods of economic forecasting (extrapolation) in conditions of difficult, instable, ambiguous, irregular or crisis dynamics of the economic situation development. To solve this problem, hybrid neuro-fuzzy techniques are best suited, which served as the basis for the author's approach and the developed NFHS for evaluating the intellectual capital of the business community "Board".

In this neuro-fuzzy hybrid system for managing IC of the business community, several features are considered – the IC of leaders, mentors and members, which are integrated into one common value using the convolution procedures of the fuzzy logic apparatus.

The organizational and economic mechanism of managing the intellectual capital of the business community can be incorporated in the structure of the management system, which determines the regular firm connections and relations within the community, the main directions of managerial influence, that provide the integrity of the whole mechanism. Like any other management system, the organizational and economic mechanism of managing the intellectual capital consists of two subsystems: ruling and ruled, both being in dialectic interrelation. The ruled subsystem in this case is presented by the intellectual capital and its functions. The structure and the content of the ruling system is the basis of the IC management mechanism of the business community and is realized by the developed NFHS.

The developed neuro-fuzzy hybrid system for managing the intellectual capital of the business community "Board" can be regarded as a typical one for the given class of problems. The methods underlying it can be applied to evaluate other economic processes characterized by fuzzy relations between input and output parameters, significant difficulties at formalization of influence factors, possibility to use experts' linguistic expressions for building a system, etc.

References

1. LETA Capital, & Devar. (2021). *State Of Phygital*. https://global-uploads.webflow.com/6198cb076e036ab5a326fa84/623843d93006dc23e1b05264_STATE%20OF%20PHYGITAL%202021%20BY%20LETA%20AND%20DEVAR.pdf

2. Bontis, N. (2001). Assessing knowledge assets: a review of the models used to measure Intellectual Capital. *International Journal of Management Review*, *3*(1), 41–60. https://doi.org/10.1111/1468-2370.00053

3. Galbraith, J. K. (1967). *The New Industrial State*. Houghton Mifflin.

4. Sakaiya, T. (1991). *The Knowledge-Value Revolution, or a History of the Future*. Kodansha International.

5. Petty, R., & Guthrie, J. (2000). Intellectual capital literature review: Measurement, reporting and management. *Journal of Intellectual Capital*, *1*(2), 155–176. https://doi.org/10.1108/14691930010348731

6. Edvinsson, L., & Malone, M. (1997). *Intellectual Capital: Realizing Your Company's True Value by Finding Its Hidden Brainpower*. Harper Business.

7. Kozlovskyi, S., Baidala, V., Tkachuk, O., & Kozyrska, T. (2018). Managament of Sustainable Development of the Agrarian Sector of the Regions of Ukraine. *Montenegrin Journal of Economics*, *14*(4), 175–190. https://doi.org/10.14254/1800-5845/2018.14-4.12

8. Kasiewicz, S., Rogowski, W., & Kicińska, M. (2006). *Kapitał intelektualny. Spojrzenie z perspektywy interesariuszy [Intellectual capital. View from the perspective of stakeholders]*. Oficyna Ekonomiczna. [in Polish]

9. Tobin, J. (1969). A general equilibrium approach to monetary theory. *Journal of Money Credit and Banking*, *1*(1), 15–29. https://doi.org/10.2307/1991374

10. Kaldor, N. C. (1966). Marginal Productivity and the Macro-Economic Theories of Distribution: Comment on Samuelson and Modigliani. *The Review of Economic Studies*, *33*(4), 309–319. https://doi.org/10.2307/2974428

11. Chen, S., & Dodd, J. L. (1997). Economic Value Added (EVA™): An Empirical Examination of a New Corporate Performance Measure. *Journal of Managerial Issues*, *9*(3), 318–333. http://www.jstor.org/stable/40604150

12. Finegan, P. T. (1989). Financial incentives resolve the shareholder-value puzzle. *Corporate Cashflow*, *October*, 27–32.

13. Tully, S., & Hadjian, A. (1993). The real key to creating wealth. *Fortune*, *128*(6), 38–50.

14. Edvinsson, L., & Malone, M.S. (2001). *Kapital intelektualny [Intellectual capital]*. Wydawnictwo Naukowe PWN. [in Polish]

15. Sveiby, K.-E., Annell, E., Axelsson, S., Emilsson, P.-M., Karlsson, H., Wangerud, C.J., & Vikström, S. (1990). *The Invisible Balance Sheet*. Affarsvarlden-Ledarskap.

16. Buenechea-Elberdin, M., Kianto, A., & Sáenz, J. (2017). Intellectual capital drivers of product and managerial innovation in high-tech and low-tech firms. *R&D Management*, *48*(3), 290–307. https://doi.org/10.1111/radm.12271

17. Carnegie, G. D., & Napier, C. J. (2017). The accounting, auditing & accountability journal community in its 30th year. *Accounting, Auditing &*

Accountability Journal, *30*(8), 1642–1676. https://doi.org/10.1108/AAAJ-12-2016-2804

18. Malcolm, D. G., Roseboom, J. H., Clark, C. E., & Fazar, W. (1959). Application of a Technique for Research and Development Program Evaluation. *Operations Research*, *7*(5), 646–669. https://doi.org/10.1287/opre.7.5.646

19. Magee, J. F. (1964). Decision trees for decision making. *Harvard Business Review, 42*(4), 126-138. https://hbr.org/1964/07/decision-trees-for-decision-making

20. Kelley, J. E., Walker, M. R., & Sayer, J. S. (1989). The origins of CPM: a personal history. *PM Network*, *3*(2), 7–22. https://www.pmi.org/learning/library/origins-cpm-personal-history-3762

21. Goldratt, E. M. (1997). *Critical Chain*. North River Press.

22. Fleming, Q. W., & Koppelman, J. M. (2010). *Earned Value Project Management* (4th ed.). Project Management Institute.

23. Kozlovskyi, S., Mazur, H., Vdovenko, N., Shepel, T., & Kozlovskyi, V. (2018). Modeling and forecasting the level of state stimulation of agricultural production in Ukraine based on the theory of fuzzy logic. *Montenegrin Journal of Economics*, *14*(3), 37–53. https://doi.org/10.14254/1800-5845/2018.14-3.3

24. Matviychuk, A., Lukianenko, O., & Miroshnychenko, I. (2019). Neuro-fuzzy model of country's investment potential assessment. *Fuzzy economic review*, *24*(2), 65–88. https://doi.org/10.25102/fer.2019.02.04

25. Turner, R. (2014). *Handbook of Project-Based Management: Leading Strategic Change in Organizations* (4th ed.). McGraw-Hill.

26. Antoniuk, L., Gernego, Iu., Dyba, V., Polishchuk, Ye., & Sybirianska, Yu. (2017). Barriers and opportunities for hi-tech innovative small and medium enterprises development in the 4th industrial revolution era. *Problems and Perspectives in Management, 15*(4), 100-113. https://doi.org/10.21511/ppm.15(4).2017.09

27. Zavidna, L., Trut, O., Slobodianiuk, O., Voronenko, I., & Vartsaba, V. (2022). Application of anti-crisis measures for the sustainable development of the regional economy in the context of doing local business in a post-COVID environment. *International Journal of Sustainable Development and Planning*, *17*(5), 1685-1693. https://doi.org/10.18280/ijsdp.170535

28. Balan, V. (2020). Zastosuvannia dynamichnoho nechitkoho space-analizu dlia formuvannia stratehii pidpryiemstva [Application of dynamic fuzzy space-analysis for forming enterprise strategies]. *Neiro-Nechitki Tekhnolohii Modelyuvannya v Ekonomitsi (Neuro-Fuzzy Modeling*

Techniques in Economics), 9, 26-64. http://doi.org/10.33111/nfmte.2020.026 [in Ukrainian]

29. Kozlovskyi, S., Butyrskyi, A., Poliakov, B., Bobkova, A., Lavrov, R., & Ivanyuta, N. (2019). Management and comprehensive assessment of the probability of bankruptcy of Ukrainian enterprises based on the methods of fuzzy sets theory. *Problems and Perspectives in Management*, *17*(3), 370-381. http://dx.doi.org/10.21511/ppm.17(3).2019.30

30. U.S. Chamber of Commerce. (2021). *Small Business Index, Q4 2021. Index Reaches Pandemic-Era High, as Many See Brighter Future*. https://www.uschamber.com/sbindex/2021-Q4

31. Syniehub, P. (2022). Kontseptsii stvorennya ta pryznachennya biznes-spil'not v ekonomichnomu prostori [Concepts of creation and purpose business communities in the economic space]. *Ekonomika ta suspil'stvo (Economy and Society), 35*, Article 32. https://doi.org/10.32782/2524-0072/2022-35-32 [in Ukrainian]

32. Board. (2022). *Spil'nota Board [Community Board]*. Retrieved July 7, 2022, from https://board.business/

33. Kozlovskyi, S., Nikolenko, L., Peresada, O., Pokhyliuk, O., Yatchuk, O., Bolgarova, N., & Kulhanik, O. (2020). Estimation level of public welfare on the basis of methods of intellectual analysis. *Global Journal of Environmental Science and Management*, *6*(3), 355–372. https://doi.org/10.22034/gjesm.2020.03.06

34. Azarova, A., Radomska, L., & Azarova, L. (2020). Neuro-fuzzy modelling of economic specialties students' speech-communicative professional competence. *Neiro-Nechitki Tekhnolohii Modelyuvannya v Ekonomitsi (Neuro-Fuzzy Modeling Techniques in Economics), 9*, 3-25. http://doi.org/10.33111/nfmte.2020.003

35. Rotshtein, A. P., Shtovba, S. D. (2002). Influence of Defuzzification Methods on the Rate of Tuning a Fuzzy Model. *Cybernetics and Systems Analysis*, *38*, 783–789.

36. Matviychuk, A. (2010). Bankruptcy prediction in transformational economy: discriminant and fuzzy logic approaches. *Fuzzy economic review*, *15*(1), 21–38. https://doi.org/10.25102/fer.2010.01.02

37. Zadeh, L. A. (1994). Soft Computing and Fuzzy Logic. *IEEE Software*, *11*(6), 48–56. https://doi.org/10.1109/52.329401

38. Zadeh, L. A. (1997). Toward a theory of fuzzy information granulation and its centrality in human reasoning and fuzzy logic. *Fuzzy Sets and Systems*, *90*(2), 111–127. https://doi.org/10.1016/S0165-0114(97)00077-8

39. Rotshtein, A. (1998). A. Design and Tuning of Fuzzy Rule-Based Systems for Medical Diagnosis. In H.-N. Teodorescu, A. Kandel, & L. C. Jain (Eds.), *Fuzzy and Neuro-Fuzzy Systems in Medicine* (pp. 243-289).

CRC Press. https://www.researchgate.net/publication/245881295_Design_and_Tuning_of_Fuzzy_Rule-Based_Systems_for_Medical_Diagnosis

40. Rotshtein, A. P., & Shtovba, S. D. (2009). Modeling of the Human Operator Reliability with the Aid of the Sugeno Fuzzy Knowledge Base. *Automation and Remote Control*, *70*, 163–169. https://doi.org/10.1134/S0005117909010123

41. Pratap, R. (2016). *Getting started with MATLAB 5: A quick introduction for scientists and engineers* (7th ed.). Oxford University Press.

42. Matviychuk, A. (2012). Obgruntuvannia vyboru naukovoi spriamovanosti zhurnalu (vstupne slovo holovnoho redaktora) [Rationale for Choosing the Scientific Focus of the Journal (Introduction by the Chief Editor)]. *Neiro-Nechitki Tekhnolohii Modelyuvannya v Ekonomitsi (Neuro-Fuzzy Modeling Techniques in Economics), 1*, 7–36. http://doi.org/10.33111/nfmte.2012.007 [in Ukrainian]

43. Kozlovskyi, S. V., & Syniehub, P. S. (2022). Kognetyvna otsinka intelektual'nogo kapitalu ekonomichnykh system v ekonomitsi znan' [Cognitive assessment of intellectual capital of economic systems in the knowledge economy]. *Ekonomika ta derzhava*, *8*, 48–55. https://doi.org/10.32702/2306-6806.2022.8.48 [in Ukrainian]

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MODELING THE VALUES OF REFLEXIVE CHARACTERISTICS OF AGENTS WITHIN THE MANAGEMENT OF HERD BEHAVIOR AT THE ENTERPRISES

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The central place at the formation of agent behavior at enterprises is the study of decision-making procedures and factors that mediate their choice. To determine the values of the reflexive characteristics of agents in the framework of management of herd behavior at enterprises a new approach is proposed based on questionnaire methods, the apparatus of the theory of fuzzy sets and neural network modeling.

The determination of the values of reflexive characteristics of agents is carried out by the formation of fuzzy sets in the framework of the theory of L. Zadeh based on the results of a questionnaire of agents in selected areas. The agents are distributed by the Kohonen map into groups in order to numerically determine the values of their reflexive characteristics based on formed fuzzy sets. An important applied value in interpreting the results of the Kohonen SOM clustering is the ability to obtain representatives of specific clusters and average values of their characteristics, which are determined by the parameters of the network neurons and represent cluster centers. As a result of the clustering of input data vectors by directions of determining the values of the reflexive characteristics of agents, typical values of the required parameters are obtained for agents-representatives of clusters. The values of the reflexive characteristics of agents can be used to evaluate the results of decision-making by agents using the functions of reflexive choice to ensure effective management of manifestations of herd behavior at enterprises.

The proposed modeling methodology will allow to identify the prerequisites for the manifestation of herd behavior at enterprises and the potential circle of agents for the formation of adequate managing actions in the process of ensuring effective management of herd behavior and achieving the goals of the enterprise.

Keywords: *modeling, reflexive characteristics, agent, herd behavior, enterprise, questionnaires, fuzzy sets, self-organizing map*

JEL Classification: C02, C45, C52, C53, D91

Introduction

The study of decision-making procedures and the factors determining their choice occupies a central place in the formation of the behavior of agents at enterprises. In modern conditions of managing enterprises, which are determined by the instability of the external and internal environment and the need to take into account and process a large amount of information from various information sources. It becomes especially relevant to take into account irrational components in the decision-making process. If there is not enough information to make decisions or if there is no possibility of its independent processing, the decisions made by agents at enterprises can be based on the observed decisions or representations of other agents, which creates conditions for manifestations of herd behavior. The prerequisites for the manifestation of herding at enterprises are due to cognitive distortions in judgments, among which one can single out conformism, the effect of familiarity with the object, preference for zero risk, submission to authority, etc.

Indeed, the above cognitive distortions reflect the essence of reflexive processes in decision-making by economic agents in the process of herd behavior and affect not only the decision-making process, but also its result. Nobel laureates of different years have been investigating this issue. Thus, M. Allais was one of the first in his works to refute the rationality of the behavior of economic agents [1]. D. Kahneman and A. Tversky [2] proved that the same decision can have different values for agents with respect to any reference point (for example, from the initial state of the individual or from the situation in which the decision was made). R. Thaler studied cognitive distortions in judgments that manifest themselves in the decision-making process of economic agents and can lead to inaccurate judgments, incorrect interpretation of information or demonstration of irrationality in behavior and economic decision-making [3].

Such effects of irrational behavior and associated manifestations of herd behavior are actively studied by scientists in a variety of subject areas: in financial [4] and consumer's [5, 6] markets, bank lending [7], cooperative behavior of people in society [8], etc. For example, in article [8] modeling of human behavior types with usage of Kohonen self-organizing maps is carried out on the basis of laboratory experiments "Public good" outcomes, and interpretation of the results in terms of "reciprocity" and "free-rider" behavioral hypotheses. The works of V. Danich and K. Shekhovtsova [9], S. Solodukhin [10], I. Stashkevych [11, 12] and others are devoted to studies of the influence of reflexive components on the decision-making process and related manifestations of herd behavior at the level of enterprises.

So, in [9] it is pointed out that there is an indirect impact on the activities of enterprises through fluctuations in exchange rates in financial markets and the associated currency panics and hype. S. Solodukhin conducted research on the manifestations of the herd behavior of agents in the internal and external environment of enterprises [10], in which the author substantiates the expediency of forming a base of typical models for studying the subject area. However, it should be noted that the models presented in [9, 10] are quite general, which implicitly take into account the reflexive characteristics of the decision-making process by agents. In addition, the authors do not divide the features of accounting for the selected characteristics within the proposed models and present them as generalized categories and parameters, which makes it difficult to use the models given in [9, 10] to solve the problems of managing herd behavior at enterprises.

In [11, 12] the authors proposed conceptual provisions for minimizing the resistance of personnel to organizational changes at enterprises, within the framework of which they developed: an approach to assessing the level of support for organizational changes in the team after information interaction between employees; approach to decision-making in the field of management by minimizing the resistance of personnel to organizational changes at the enterprise using elements of herd behavior based on a reflexive approach.

In [11] the authors considered the influence of conformism, as a special case of the manifestation of herd behavior, on the results of decision-making by agents, but did not present a methodology for determining the values of reflexive characteristics of agents, which should be decisive in managing the manifestations of herd behavior in enterprises. Similarly, the works [13, 14] examines how the reflexive characteristics of agents affect the level of agreement of goals in the group without indicating specific methods for determining such characteristics.

Thus, due to the lack of effective mechanisms for identifying and numerically assessing the values of reflexive characteristics of agents, in order to determine the main parameters of the decision-making process by agents and effectively manage the manifestations of herd behavior at enterprises, it is necessary to develop an appropriate methodology using methods of economic and mathematical modeling.

The objective of the article is to develop a new method for assessing the values of reflexive characteristics of agents within the framework of management of herd behavior at enterprises using methods of economic and mathematical modeling.

Methodology

Understanding herd behavior as a result of decision-making strategy by management agents, which is not based on rational judgments, but is focused on imitating more authoritative and/or other economic agents when making decisions, the main reflexive components of the decision-making process by economic subjects are defined in [12-14]: awareness of agents, their competence, authority, propensity to imitate and intentional orientation.

Considering the qualitative nature of these categories, the subjectivity of their assessments and weak formalization, there is a need to use mathematical tools that are designed to process fuzzy, linguistically defined characteristics. An effective tool for solving such problems is the theory of fuzzy sets by L. Zadeh [15].

Moreover, each of these categories depends on many factors influencing it, the list of which and the degree of influence are also not determined by any objective circumstances and can be set by analysts depending on their own understanding of their essence. Dependence on the subjective opinion of individual experts can be reduced by using special modeling methods that can identify patterns in the structure of an array of heterogeneous data when there are no predetermined values of the resulting indicator.

In such conditions, the cluster approach is the most suitable tool for searching for hidden patterns in sets of explanatory variables. As a result, it becomes possible to form fairly homogeneous groups of studied objects characterized by similar properties.

Consequently, within the framework of the toolkit for diagnosing manifestations of herd behavior, based on the fuzzy sets formed at the first stage, clustering is carried out both in order to determine the numerical values of the degree of awareness, competence, authority, propensity to imitate and intentional orientation of agents, and for the identification of a potential circle of agents on which the control actions of the mechanism of reflexive management of herd behavior will be directed.

The sequence of assessing the values of the characteristics of agents within the framework of our concept of modeling processes of reflexive management of herd behavior at enterprises includes the following main stages:

1. Questionnaire of agents according to directions of assessing the reflexive characteristics.
2. Formation of fuzzy sets for all characteristics based on the results of questioning agents.
3. Clustering agents according to directions of identifying reflexive characteristics.
4. Determination of the values of reflexive characteristics of agents and the potential circle of agents for reflexive management of herd behavior to achieve goals in the enterprise.

Let's consider each of the stages in more detail.

Due to the fact that in the process of manifestation of herd behavior the same agent can be both a managed and a managing, we will further use the term "management agent".

The determination of the values of the characteristics of the agents will be carried out by the method of questionnaires in the directions of identifying the relevant parameters within the framework of the object model of reflexive management of herd behavior at enterprises [13, 14].

To do this, questionnaires are initially drawn up according to five directions of identification:

α_{it} – agent's awareness of the *i*-th agent at the moment of time *t*;

γ_{it} – competence of the *i*-th management agent at the moment of time *t*;

β_{it} – authority of the *i*-th management agent at the moment *t*;

ω_i – propensity to imitate the *i*-th agent;

v_{it} – estimates of intentions (the value of a particular decision for a particular management agent) of the *i*-th agent at the moment of time *t*.

Let the questionnaire for each of the directions includes *K* questions $k = \overline{1,K}$, each of which contains a list of *L* possible answers $l = \overline{1,L}$. At the same time, the questions of the questionnaire should be formed in such a way that the options for answers to them by the respondents (agents) decrease the value of the degree of a particular characteristic as they descend. Answers to questions should be formulated variably and unambiguously so, that the respondent can choose one of the listed options.

To compose questions in the area of revealing reflexive characteristics, one can use, for instance, the studies of the famous British psychologist R. Cattell [16] and D. McClelland competence tests [17]. In addition, we assign a linguistic term to each of the answer options, which characterizes the degree of approximation of the value of a particular characteristic to its maximum possible value. To formalize the degree of such membership and further use within the framework of the mechanism of reflexive management of herd behavior at enterprises [14], we apply the theory of fuzzy sets by L. Zadeh [15], which is widely used by researchers to solve various types of problems of intellectual data processing using linguistic variables and qualitative characteristics of research objects. L. Zadeh expanded the classical concept of a set, assuming that the characteristic function (membership function for a fuzzy set) can take any values in the interval [0; 1].

To survey agents, questionnaires will be used that implement, respectively [14]:

methodology for determining the propensity to imitate and authority of agents, based on the modified structure of the questionnaire by R. Cattell [16];

methodology for determining the competence of management agents in enterprises based on the modified structure of the D. McClelland questionnaire [17], as well as competence clusters of L. Spencer and S. Spencer [18];

a method for determining the value of a decision for a management agent based on the prospect theory of D. Kahneman and A. Tversky [2] and considering a decision with respect to any reference point (the personal well-being of the agent and the enterprise);

a method of assessing awareness, which is based on identifying the degree of reliable knowledge of the agent about the actual state of the object (alternatives of the decision) and the circumstances affecting it.

To determine the propensity to imitate and the authority of agents, we will use the elements of the 16-factor personality model of R. Cattell [16]. The British psychologist R. Cattell in his research proposed a model of personality and created an appropriate psychodiagnostic technique based on a questionnaire that allows you to evaluate each of these factors. In the framework of our study, we will use elements of the methodology of R. Cattell (form A), which allows us to determine the specificity of the character, inclinations and interests of the individual. At the same time, to assess the agent's propensity to imitate, we will use the adapted questionnaires of R. Cattell according to the clusters identified within the framework of the methodology, which correspond to the characteristics of the agents' behavior:

cluster E, by means of which the conformity / dominance of the agent is assessed (adapted for use in determining the values of reflexive characteristics of agents in the process of managing herd behavior in enterprises; adaptation consists in changing the direction of assessing the results of the survey, i.e. the highest value of points is interpreted as a high degree of propensity to imitate, and the least – as low);

cluster Q1, by means of which the conservatism / radicalism of the agent is assessed (note that the increased degree of radicalism of the individual contributes to the rapid decision-making on imitation);

cluster Q2, by means of which the dependence on the group / self-sufficiency is assessed (similarly to cluster E, it is adapted for use in determining the values of reflexive characteristics of agents in managing herd behavior at enterprises; adaptation consists in changing the direction of assessing the results of the survey, i.e. the highest score interpreted as a high degree of dependence on the group, and the smallest – as low).

So, to assess the agent’s propensity to imitate in the decision-making process, the questionnaires contain $k_\omega = \overline{1,33}$ questions, each of which includes a list of possible answers $l_{k_\omega} = \overline{1,3}$, according to the method adapted by R. Cattell. In this case, the function $\mu(x^{k_\omega l_{k_\omega}})$ takes values in some linearly ordered set of memberships $M_\Omega = \{0;\ 0.5;\ 1\}$. For example, for question 28 of the questionnaire about the propensity to imitate “It is easier for me to solve a difficult question or problem”:

$$\mu(x^{28_\omega l_{28_\omega}}) = \begin{cases} 0, & l_{28_\omega} = 1 \mid \textit{if I think about them alone}; \\ 0.5, & l_{28_\omega} = 2 \mid \textit{right in the middle}; \\ 1, & l_{28_\omega} = 3 \mid \textit{if I discuss them with others}. \end{cases}$$

Thus, the set Ω contains a complete list of membership functions for all 33 questions and answer options to guide the identification of the propensity to imitate management agents.

Similarly, fuzzy sets are formed to assess the authority of agents within the framework of the mechanism of reflexive management of herd behavior at enterprises. At the same time, to assess the authority of the agent, adapted questionnaires by R. Cattell according to the 16-factor model of personality (Form A of the questionnaire) are used, namely questions corresponding to:

cluster Q3, with the help of which low / high conceit of the agent is estimated;

cluster E, which evaluates the conformity / dominance of the agent (the highest score is interpreted as a high degree of dominance in the group, and the lowest – as low).

According to the adapted method of R. Cattell, the developed questionnaires contain $k_\beta = \overline{1,3}$ questions regarding the assessment of the authority of agents, each of which contains a list of possible answers $l_{k_\beta} = \overline{1,3}$. The function $\mu(x^{k_\beta l_{k_\beta}})$ takes values in some linearly ordered set $M_B = \{0;\ 0.5;\ 1\}$. The set B contains a complete list of membership functions for all questions and answer options to guide the identification of the authority of management agents.

We will determine the competence of management agents at enterprises using the modified structure of the D. McClelland questionnaire [17] and competence clusters of L. Spencer and S. Spencer [18]. Here, to assess the competence of agents, the possibility of using generalized competence models for technical specialists, proposed in [18] as a development of the ideas of D. McClelland, is considered. The model highlights key competencies, among which the most significant are: achievement, impact and influence, conceptual and analytical thinking and initiative. Thus, to assess the competence of agents, the questionnaires contain $k_\gamma = \overline{1,19}$ questions, each of which includes a list of possible answers $l_{k_\gamma} = \overline{1,5}$. Accordingly, the function $\mu\left(x^{k_\gamma l_{k_\gamma}}\right)$ takes values in some linearly ordered set $M_\Upsilon \in [0;1]$ from the membership set $M_\Upsilon = \left\{0;\ 0.25; 0.5; 0.75; 1\right\}$. The set Υ contains a complete list of membership functions for all questions and answer options to identify the competence of agents.

Questionnaires and corresponding fuzzy sets in the direction of awareness contain questions and corresponding answer options developed on the basis of understanding the definition of agent awareness, which implies the degree of his reliable knowledge about the actual state of the object (alternatives of the decision being made) and the circumstances affecting it, and contain $k_\alpha = \overline{1,8}$ questions, each of which includes a list of possible answers $l_{k_\alpha} = \overline{1,5}$.

At the same time, the key factors are: the sources of obtaining information, the reliability of the facts and information used in the decision-making process, the frequency of using distorted information, the completeness and efficiency of obtaining the necessary information in the decision-making process and the degree of general awareness of the agent about the decision being made. The degrees of belonging are described as follows: for example, for the first question of the agent's awareness assessment questionnaire:

$$\mu(x^{1_\alpha l_{1_\alpha}}) = \begin{cases} 0, & l_{1_\alpha} = 1 \left| \begin{array}{l} \textit{I don't use sources. I use only existing} \\ \textit{knowledge}; \end{array} \right. \\ 0.25, & l_{1_\alpha} = 2 \left| \ \textit{information from management}; \right. \\ 0.5, & l_{1_\alpha} = 3 \left| \begin{array}{l} \textit{information from management and} \\ \textit{which is discussed with employees}; \end{array} \right. \\ 0.75, & l_{1_\alpha} = 4 \left| \begin{array}{l} \textit{information from management and} \\ \textit{official information resources on the topic}; \end{array} \right. \\ 1, & l_{1_\alpha} = 5 \left| \begin{array}{l} \textit{studied the topic in detail using all} \\ \textit{available official information resources.} \end{array} \right. \end{cases}$$

Moreover, in terms of the mechanism of reflexive management of herd behavior at enterprises, the membership function $\mu(x^{k_\alpha l_{k_\alpha}})$ expresses how agent *i* is informed at the moment of time *t*. The function $\mu(x^{k_\alpha l_{k_\alpha}})$ takes values in some linearly ordered set $M_A \in [0;1]$ and consists of five elements according to the number of possible answers in each of the questions: $M_A = \{0; 0.25; 0.5; 0.75; 1\}$. The set *A* contains a complete list of membership functions for all questions and answer options to identify the awareness of management agents.

In the same way, fuzzy sets are formed for the questions of questionnaires to determine the intentional orientation of agents (the value of the decision made for management agents). In this case, the value of particular decision for the agent is estimated according to the prospect theory of D. Kahneman and A. Tversky [2] and is considered relative to any reference point (the personal well-being of the agent or the enterprise).

Due to the fact that the theory of fuzzy sets in a certain sense is reduced to the theory of probability [15], the value of the membership function can be considered as the probability of covering an element, for example $x^{k_\nu l_{k_\nu}}$, by some random set. Then, from the point of view of the mechanism of reflexive management of herd behavior at enterprises $\mu(x^{k_\nu l_{k_\nu}})$ can be interpreted as the probability that agent will make a choice of some decision.

At the same time, under the fuzzy set *A* of the degree of awareness of agents at a moment *t* we will understand the set of ordered pairs made up of elements $x^{k_\alpha l_{k_\alpha}}$ of the universal set X_α and the corresponding degrees of membership $\mu\left(x^{k_\alpha l_{k_\alpha}}\right)$:

$$A=\left\{\left(x^{k_\alpha l_{k_\alpha}},\mu\left(x^{k_\alpha l_{k_\alpha}}\right)\right)\middle|x^{k_\alpha l_{k_\alpha}}\in X_\alpha,\mu\left(x^{k_\alpha l_{k_\alpha}}\right)\in M_A\right\}. \tag{1}$$

If $M_A=\{0,1\}$, that is, it consists of only two elements, then the fuzzy set can be considered as an ordinary crisp set.

Similarly, fuzzy sets will be formed for each of the other selected reflexive characteristics of agents within the framework of the mechanism of reflexive management of herd behavior at enterprises.

So, to determine the competence of the management agent, we get the set:

$$\Upsilon=\left\{\left(x^{k_\gamma l_{k_\gamma}},\mu\left(x^{k_\gamma l_{k_\gamma}}\right)\right)\middle|x^{k_\gamma l_{k_\gamma}}\in X_\gamma,\mu\left(x^{k_\gamma l_{k_\gamma}}\right)\in M_\Upsilon\right\}, \tag{2}$$

where X_γ is the universal set of $x^{k_\gamma l_{k_\gamma}}$.

To determine the authority of agents, we get a set:

$$B=\left\{\left(x^{k_\beta l_{k_\beta}},\mu(x^{k_\beta l_{k_\beta}})\right)\middle|x^{k_\beta l_{k_\beta}}\in X_\beta,\mu(x^{k_\beta l_{k_\beta}})\in M_B\right\}, \tag{3}$$

where X_β is the universal set of $x^{k_\beta l_{k_\beta}}$.

To determine the propensity of agents to imitate in the decision-making process, we obtain the following set:

$$\Omega = \left\{ \left(x^{k_\omega l_{k_\omega}}, \mu(x^{k_\omega l_{k_\omega}}) \right) \middle| x^{k_\omega l_{k_\omega}} \in X_\omega, \mu(x^{k_\omega l_{k_\omega}}) \in M_\Omega \right\}, \tag{4}$$

where X_ω is the universal set of $x^{k_\omega l_{k_\omega}}$.

In turn, to determine the intentional orientation of agents in the decision-making process at the moment of time *t*, we obtain a set:

$$I = \left\{ \left(x^{k_\nu l_{k_\nu}}, \mu(x^{k_\nu l_{k_\nu}}) \right) \middle| x^{k_\nu l_{k_\nu}} \in X_\nu, \mu(x^{k_\nu l_{k_\nu}}) \in M_I \right\}, \tag{5}$$

where X_ν is the universal set of $x^{k_\nu l_{k_\nu}}$.

So, for example, according to the results of the survey of the *i*-th agent A_i, his awareness α_{it} at the moment of time *t* will be determined by the answers $x^{k_\alpha l^*_{k_\alpha}}$, $k_\alpha = \overline{1,8}$, where the parameter $l^*_{k_\alpha}$ will be the answer chosen by the agent from the list of options L_α to the question k_α:

$$A^* = \left\{ x_{it}^{k_\alpha l^*_{k_\alpha}} \in X_\alpha \right\}, k = \overline{1,K_\alpha}. \tag{6}$$

Then, the set of fuzzy representations of the results of the questionnaire in the direction of identifying the degree of awareness of the agent will have the following form:

$$\tilde{A} = \left\{ \mu(x_{it}^{k_\alpha l^*_{k_\alpha}}) \middle| x_{it}^{k_\alpha l^*_{k_\alpha}} \in X_\alpha \right\}. \tag{7}$$

In this case, the set of fuzzy sets of agent survey results in all directions of revealing the reflexive characteristics of agents will correspond to the sets $\tilde{A}, \tilde{\Upsilon}, \tilde{B}, \tilde{\Omega}, \tilde{I}$ (Table 1).

Table 1

SETS OF FUZZY REPRESENTATIONS OF THE RESULTS OF QUESTIONNAIRES OF REFLEXIVE CHARACTERISTICS OF AGENTS

Reflexive characteristics	Sets of survey results	Sets of fuzzy representations of survey results
α_{it} – *i*-th agent's awareness at the moment *t*	$A^* = \left\{ x_{it}^{k_\alpha l^*_{k_\alpha}} \in X_\alpha \right\}$	$\tilde{A} = \left\{ \mu(x_{it}^{k_\alpha l^*_{k_\alpha}}) \middle| x_{it}^{k_\alpha l^*_{k_\alpha}} \in X_\alpha \right\}$
γ_{it} – competence of a management agent *i* at the moment *t*	$\Upsilon^* = \left\{ x_{it}^{k_\gamma l^*_{k_\gamma}} \in X_\gamma \right\}$	$\tilde{\Upsilon} = \left\{ \mu(x_{it}^{k_\gamma l^*_{k_\gamma}}) \middle| x_{it}^{k_\gamma l^*_{k_\gamma}} \in X_\gamma \right\}$
β_{it} – authority of the management agent *i* at the moment *t*	$B^* = \left\{ x_{it}^{k_\beta l^*_{k_\beta}} \in X_\beta \right\}$	$\tilde{B} = \left\{ \mu(x_{it}^{k_\beta l^*_{k_\beta}}) \middle| x_{it}^{k_\beta l^*_{k_\beta}} \in X_\beta \right\}$
ω_i – propensity to imitate of a management agent *i*	$\Omega^* = \left\{ x_{i}^{k_\omega l^*_{k_\omega}} \in X_\omega \right\}$	$\tilde{\Omega} = \left\{ \mu(x_{i}^{k_\omega l^*_{k_\omega}}) \middle| x_{i}^{k_\omega l^*_{k_\omega}} \in X_\omega \right\}$
ν_{it} – assessment of intentions of *i*-th agent at the moment *t*	$I^* = \left\{ x_{it}^{k_\nu l^*_{k_\nu}} \in X_\nu \right\}$	$\tilde{I} = \left\{ \mu(x_{it}^{k_\nu l^*_{k_\nu}}) \middle| x_{it}^{k_\nu l^*_{k_\nu}} \in X_\nu \right\}$

After obtaining the results of identifying the reflexive characteristics of agents to determine the degree of awareness, competence, value of a decision for a particular agent at the time *t*, the authority of agents and the propensity to imitate, the formed fuzzy sets must be grouped and processed so that the numerical values of the indicated parameters for each agent can be determined. And since for the task of assessing the reflexive characteristics of agents there is no generally accepted indicator and scale of its measurements, there is a need to solve the problem of searching for patterns of behavior of different groups of agents and regularities in their reactions to different influences. This problem is solved by clustering the obtained fuzzy values of reflexive characteristics in the relevant areas of analysis of the decision-making process. It should be noted that the purpose of such a clustering will be not only the numerical determination of the reflexive characteristics of agents, but also the identification of a potential circle of agents on which the control actions of the mechanism of reflexive management of herd behavior will be directed.

There is a wide range of cluster analysis methods: K-means [19], K-medoids [20], Principal Component Analysis (PCA) [21], t-Stochastic Neighbour Embedding (t-SNE) [22], Dendrogram Method [23], Dendrite Method [24], Density-Based Spatial Clustering of Applications with Noise (DBSCAN) [25], Uniform Manifold Approximation and Projection (UMAP) [26], Balanced Iterative Reducing and Clustering Using Hierarchies (BIRCH) [27], Self-Organizing Maps (SOM) [28-30] and its variation – SOM algorithm with C-Weighted Medoids for dissimilarity data (RBSOM-CWMdd) and Batch SOM algorithm with Adaptive Heuristic C-Weighted Medoids for dissimilarity data (RBSOM-ACWMdd) [31], etc.

Each of these methods has its own advantages and areas of application and tasks where it works best. Experimental comparisons of the effectiveness of various clustering methods are described, in particular, in the papers [31-34].

Considering the capabilities of each of the mentioned methods, the small size of the database and the fuzzy nature of the analyzed indicators, in this study the toolkit of Kohonen self-organizing maps was chosen, which, in addition to the formation of homogeneous groups of studied objects, provides a convenient tool for visual analysis of clustering results. In particular, unlike other clustering methods, the location of an object on the Kohonen map indicates to the analyst how developed the characteristic under study is in comparison with others, since the best and worst objects according to the analyzed reflexive characteristic are located in opposite corners of the SOM.

Thus, to assessing the values of reflexive characteristics in terms of determining the degree of awareness of agents, competence, authority, propensity to imitate and intentional orientation, we will use the Kohonen neural network. In this case, we will supply the values of membership functions to fuzzy sets of the results of questioning agents to the inputs of the neural network.

A self-organizing map is a neural network without feedback, which is configured using an unsupervised learning algorithm by identifying unknown patterns and structures in the given indicators of the objects under study. The learning algorithm provides a mapping of a high-dimensional space onto a low-dimensional map, while maintaining its topological structure. The topology-preserving property means that, as a result of self-organization, similar input data vectors are projected onto neurons located close to each other on the Kohonen map.

A self-organizing map is formed from neurons, each of which is connected to all neurons of the input layer (Fig. 1) [28-30].

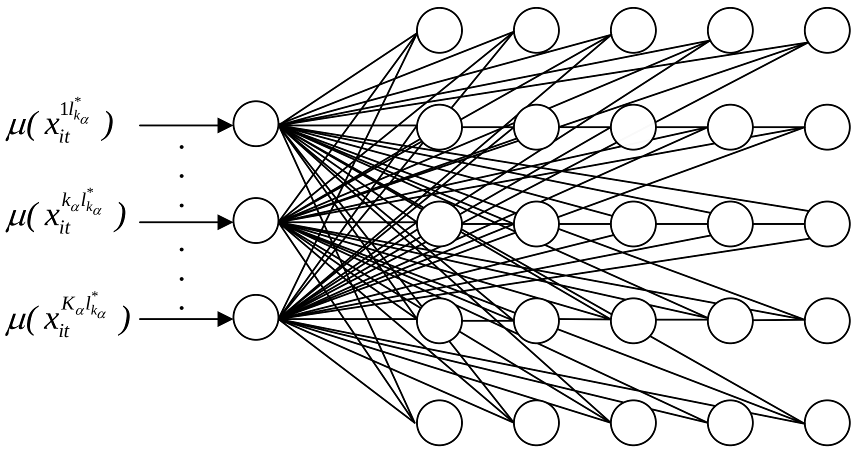


Fig. 1. The structure of the Kohonen neural network

In self-organizing maps, neurons are located at the nodes of a lattice, most often one- or two-dimensional. When constructing a two-dimensional lattice, an orthogonal or hexagonal structure is usually chosen (the hexagonal ordering of neurons on the Kohonen map makes it possible to visually represent the result of clustering objects more qualitatively).

The neurons of the input layer do not convert the input signals – they only transmit them to all elements of the self-organizing map. Each neuron of the Kohonen layer receives information regarding the object of study in the form of a vector consisting of sets obtained as a result of questioning the studied agents $\tilde{A} = \left\{ \mu(x_{it}^{k_\alpha l_{k_\alpha}^*}) \middle| x_{it}^{k_\alpha l_{k_\alpha}^*} \in X_\alpha \right\}$.

When a new data vector arrives at the input layer of the network, all neurons of the self-organizing map compete to become the winner. As a result of such a competition, the winner is the neuron that is most similar to the input data vector. According to [28], the measure of such similarity of the data vector to each neuron can be determined by calculating the Euclidean distance:

$$\left\| x - w_\alpha^j \right\| = \sqrt{\sum_{k_\alpha=1}^{K_\alpha} (x_{it}^{k_\alpha l_{k_\alpha}^*} - w_{k_\alpha}^j)^2},\ j = \overline{1, M}, \tag{8}$$

where x is an input vector that consists of answers to the questions of the agents' questionnaire $\left\{ \mu(x_{it}^{1 l_{k_\alpha}^*}); \ldots; \mu(x_{it}^{k_\alpha l_{k_\alpha}^*}); \ldots; \mu(x_{it}^{K_\alpha l_{k_\alpha}^*}) \right\}$;

w_α^j is a parameter vector of the i-th neuron of the Kohonen map, which consists of elements $\left\{ w_1^j, \ldots, w_{k_\alpha}^j, \ldots, w_{K_\alpha}^j \right\}$;

M is the number of neurons in the Kohonen map.

The winner in such a competition of self-organizing map neurons is one neuron that is most similar to the vector of input data according to the Euclidean distance (8). Its output will be one, the states of all other neurons of the SOM are equal to zero:

$$y_j = \begin{cases} 1, \left\| x - w_\alpha^j \right\| = \min\limits_{m=\underline{1,M}} \left\| x - w_\alpha^m \right\| \\ 0, \left\| x - w_\alpha^j \right\| \neq \min\limits_{m=\underline{1,M}} \left\| x - w_\alpha^m \right\| \end{cases},\ j = \overline{1, M} \tag{9}$$

Function (9) implements the "winner-take-all" rule of competition [28, 35]. After finding the neuron-winner with respect to the input data vector, its parameters and the neurons closest to it are adjusted in a certain neighborhood in the direction of the input vector, taking into account the coefficient of learning rate $\eta(\tau)$ and the function of the distance to the winner $h_{oj}(\tau)$ [28–30, 35-37]:

$$w_\alpha^j(\tau+1) = w_\alpha^j(\tau) + \eta(\tau)\cdot h_{oj}(\tau)\cdot\left[\mathrm{x}(\tau) - w_\alpha^j(\tau)\right],\ j=\overline{1,M}, \qquad (10)$$

$$h_{oj}(\tau) = exp\left[-\frac{\left\|r_o - r_j\right\|^2}{2\cdot\sigma^2(\tau)}\right], \qquad (11)$$

where r_o, r_j are the coordinates of the neuron-winner *o* and the *j*-th neuron (on the map);

$\sigma(\tau)$ is an effective width of the topological region (a specially chosen monotonically decreasing function of iteration number τ, for example, a linear or exponential).

As training progresses, the size of the topological region gradually decreases, and each new input data vector affects an ever smaller number of neurons. At the end of training, the parameters of only the nearest neighbors of the neuron-winner can be modified, and possibly only the winner itself.

The result of the tuning process will be the calculation of the parameters of the Kohonen layer neurons, which will correspond to various examples from the training set. In this way, the structure of the Kohonen map self-organizes, which acquires the ability to combine multidimensional data vectors into clusters by detecting similar statistical characteristics in them. As a result, the initial high-dimensional space is projected onto a two-dimensional map. Because self-organizing maps are characterized by the generalization property, they can recognize input examples that were not used when they were trained – the new input data vector corresponds to the map element on which it is mapped.

An important applied value of interpreting the results of Kohonen SOM clustering is the possibility of obtaining representatives of specific clusters and calculating their average values, which are determined by the network neurons parameters and represent the centers of clusters. Next, the value of the corresponding reflexive characteristics of each of the agents in the obtained clusters after processing by the neural network will be given the value of the parameters of the neuron that determines the center of the cluster. Thus, as a result of the classification of the input vectors of data according to the directions of determining the values of the reflexive characteristics of the agents, we will get the typical values of the required parameters for agents representing a particular cluster [12-14]. These clusters correspond to different patterns of agents' characteristics, which provides reasoned grounds for considering the clusters to correspond to individual classes of agents' reflexive behavior.

Thus, as a result of neural network processing of data from agent questionnaires in the direction of determining the degree of awareness of agents, we will obtain a set of parameter values $\overline{A}=\{\alpha_{it}\}, i=\overline{1,N}$. It was previously determined that from the point of view of the concept of reflexive management of herd behavior at enterprises, we will interpret the parameters $x_{it}^{k_\alpha l_{k_\alpha}}$ as the probability, that at the moment of time *t* the agent *i* is fully informed about the area of the decision being made. In this case, the translation of the obtained values α_{it} into the initial metric of linguistic parameters is not necessary.

Similarly to the considered example of clustering using self-organizing maps, after processing the results of the questionnaire in the directions of determining competence, authority, propensity to imitate and intentional directions (decision value) of agents, we obtain the following sets:

$\overline{\Upsilon}=\{\gamma_{it}\}, i=\overline{1,N}$ – set of values that determine the competence of management agents at the moment of time *t*;

$\overline{B}=\{\beta_{it}\}, i=\overline{1,N}$ – a set of values that determine the authority of management agents at the time *t*;

$\overline{\Omega}=\{\omega_i\}, i=\overline{1,N}$ – a set of values that determine the propensity to imitate agents;

$\overline{I}=\{v_{it}\}, i=\overline{1,N}$ – from the point of view of the concept of reflexive management of herd behavior at enterprises, v_{it} can be interpreted as an intentional orientation to make a choice of a certain decision for a specific agent *i* (or as a probability that at the moment *t* agent *i* is ready to make a choice of certain decision).

Experiment results

We will test the proposed approach for calculating the reflexive characteristics of agents in the framework of managing herd behavior at Novokramatorsky Mashinostroitelny Zavod using the example of agreeing on a decision on the choice of a commercial offer for suppliers of components for the manufacture of an electric overhead foundry crane.

The manufacturing of engineering products, in particular cranes, is a science-intensive and expensive process. At the same time, on average, one engineering product of the plant accounts for about 50% of purchased components. To organize such purchases for each of the projects, tenders are held for suppliers and options for commercial proposals are drawn up for the full list of necessary components for the order. Thus, the decision by the tender commission to select suppliers for the purchase of components for the production of a crane from two options of commercial proposals is an extremely important decision due to the high cost of purchased parts, which necessitates the assessment of the reflexive characteristics of agents, including for the management of the agents' decision-making process.

The tender commission consists of: 1 chairman of the tender commission; 3 representatives of the audit commission; 1 accounting representative; 1 lead design engineer; 1 constructor of the 1st category; 2 representatives of the pricing and cost management department; representatives of the procurement department in the areas of purchase of components, including 3 representatives of the bureau of purchase of electrical equipment, 2 representatives of the bureau of purchase of gearboxes, 2 representatives of the bureau of purchase of hardware products, 2 representatives of the bureau of purchase of rubber products, 2 representatives of the bureau of purchase of bearings.

For the convenience of carrying out calculations and analyzing the results obtained, we denote the agents conditionally as Agent 1, Agent 2, etc. up to 20 by the number of agents participating in the approval of commercial proposals, and assign them the appropriate indexes $i = \overline{1,20}$.

The data of the survey of agents regarding the decision to choose a commercial proposal for the purchase of components for an electric overhead foundry crane, according to the questionnaires in the direction of identifying the degree of awareness of agents, converted into membership functions, are given in Table 2.

Table 2

THE RESULTS OF THE SURVEY OF AGENTS IN THE DIRECTION OF IDENTIFYING THE REFLEXIVE CHARACTERISTIC "AWARENESS" (SET A^*)

№ of question k_α / Agent i	1	2	3	4	5	6	7	8
Agent 1	0	0.25	0.75	0.5	0.75	0.5	0.75	1
Agent 2	1	1	1	0.5	0.5	0	0.75	0.5
Agent 3	0.5	0.75	1	0.5	0.75	1	1	1
Agent 4	0	0.5	1	0.75	0.75	0.75	0.75	1
Agent 5	1	1	0.5	0.75	0.75	0.25	0.75	0.25
Agent 6	0.75	1	1	0.75	0.5	0	0.5	0.5
Agent 7	0	0.75	1	0.75	0	0.75	0.25	0.5
Agent 8	1	0	1	1	0.25	0.25	0.75	1
Agent 9	1	1	0.75	0.5	0.5	0.5	0	0.75
Agent 10	1	1	0.5	0.5	1	0.5	0.75	1
Agent 11	0.5	0.75	0.75	0.75	0.75	0.5	0.5	1
Agent 12	0.5	0.75	1	1	0.5	0.75	1	0.25
Agent 13	1	0.25	1	0.5	0	0.75	0.5	0.5
Agent 14	1	0	0.75	0	1	1	0.5	0.75
Agent 15	0.5	0.75	1	0.75	0.75	0.5	0.75	0.5
Agent 16	0.25	0.5	0.75	0.75	0.75	0.5	0.5	0.75
Agent 17	0.75	0.25	0.75	0.5	0.5	0.75	0.5	1
Agent 18	0.75	0.25	1	0.75	1	0.25	0	0.5
Agent 19	0.5	0.75	0.5	0.75	1	0.25	0.75	0.5
Agent 20	0.5	0.25	0	1	1	0.75	0.5	1

Similar tables based on the results of questioning agents are calculated for all areas of revealing the reflexive characteristics of agents. Note, that since membership functions describe possible answers ranging from 0 to 1, then preliminary data normalization is not required for further calculations and analysis.

In the framework of this study, to determine the values of the reflexive characteristics of agents in the process of managing herd behavior at enterprises using Kohonen maps, we will use the analytical platform Deductor Studio. Fig. 2 shows the self-organizing map built on the basis of the data of Table 2, classifying agents according to their answers to questionnaires in the direction of revealing the reflexive characteristics "awareness".

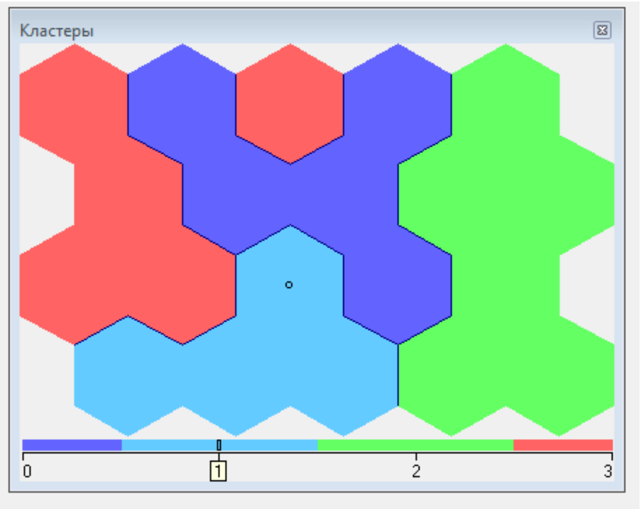


Fig. 2. Clustering of agent survey results in the direction of awareness

As a result of clustering using the Kohonen map, 4 clusters were obtained (0–3, the numbering of which can be seen from the coloring on the horizontal bottom line).

Let us analyze the distribution of control agents between clusters. As can be seen in Fig. 3, there are 4 agents in cluster 0: 9, 10, 14 and 17.

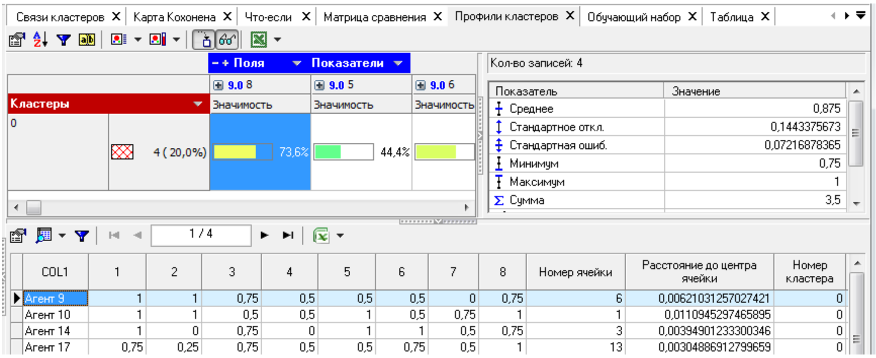


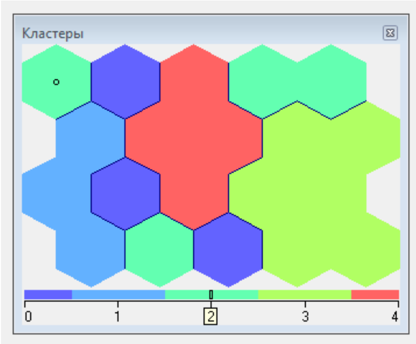
Fig. 3. Characteristics of the cluster 0 of SOM clustering results in the direction of revealing agent awareness

So, according to the proposed method, to numerically determine the awareness of agents, we assign the average value among all indicators, characterizing awareness, for agents who are included in the cluster. Then the value of the required reflexive characteristic "awareness" for each of the cluster agents will be $\alpha_{9t} = \alpha_{10t} = \alpha_{14t} = \alpha_{17t} = 0{,}875$.

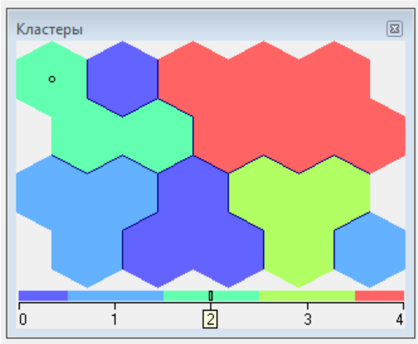
Similarly, 4 agents hit into cluster 1: 7, 8, 12, and 13. Accordingly, we assign the average value of all membership functions over the cluster to the awareness values of these four agents $\alpha_{7t} = \alpha_{8t} = \alpha_{12t} = \alpha_{13t} = 0{,}5625$. Cluster 2 includes 6 agents: 1, 3, 4, 11, 16 and 20, whose awareness values will be assigned the cluster average $\alpha_{1t} = \alpha_{3t} = \alpha_{4t} = \alpha_{11t} = \alpha_{16t} = \alpha_{20t} = 0{,}9583$. Cluster 3 includes 6 agents: 2, 5, 6, 15, 18, and 19. Accordingly, we assign $\alpha_{2t} = \alpha_{5t} = \alpha_{6t} = \alpha_{15t} = \alpha_{18t} = \alpha_{19t} = 0{,}4583$ to the values of their awareness characteristics.

The results of clustering with self-organizing maps to determine the competence, the authority, the propensity of agents to imitate and decision value of agents according to the results of the survey are shown in Fig. 4.

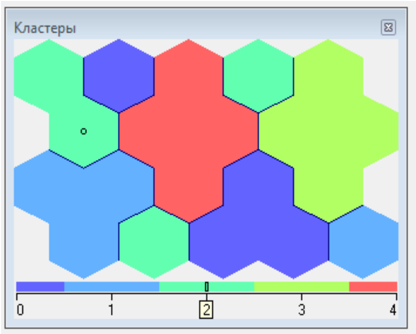
A summary table of the values of reflexive characteristics of agents based on the results of a survey at Novokramatorsky Mashinostroitelny Zavod is presented in Table 3.



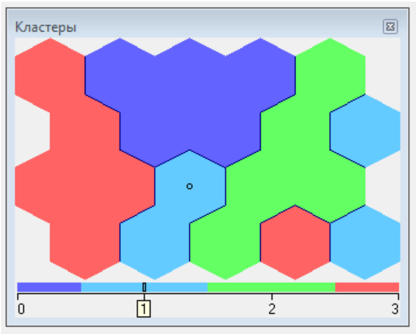
a) competence



b) authority



c) propensity to imitate



d) decision value

Fig. 4. The results of clustering by the self-organizing maps according to the indicators of reflexive characteristics of agents

In Table 3, agent 1 corresponds to the chairman of the tender commission. The values of his reflexive characteristics indicate that he enjoys authority (authority $\beta_{1t} = 0{,}83$), is competent (competence $\gamma_{1t} = 0{,}8$), is interested in choosing commercial offer No. 1 (decision value $v_{1t} = 0{,}7083$), is sufficiently informed (awareness $\alpha_{1t} = 0{,}9583$) and his propensity to imitate is quite low ($\omega_{1t} = 0{,}625$). Agent 1 in the considered example is the managing center, which is interested in the collegial acceptance of commercial offer No. 1 for the organization of the purchase of components for the crane by all agents.

Table 3

VALUES OF REFLEXIVE CHARACTERISTICS OF AGENTS OBTAINED AS A RESULT OF DATA PROCESSING BY KOHONEN MAPS

Agent *i*	**Awareness** $\overline{A}=\{\alpha_{it}\}$	**Competence** $\overline{\Upsilon}=\{\gamma_{it}\}$	**Authority** $\overline{B}=\{\beta_{it}\}$	**Propensity to imitate** $\overline{\Omega}=\{\omega_i\}$	**Decision Value** $\overline{I}=\{v_{it}\}$
Agent 1	0.9583	0.8	0.83	0.625	0.7083
Agent 2	0.4583	0.375	0.167	0.9	0.15
Agent 3	0.9583	0.375	0.167	0.4	0.65
Agent 4	0.9583	0.8	1	0.9	0.65
Agent 5	0.4583	0.67	0.625	1	0.5625
Agent 6	0.4583	0.8	0.5	0.625	0.7083
Agent 7	0.5625	0.167	1	0.4	0.5625
Agent 8	0.5625	0.8	1	0.625	0.7083
Agent 9	0.875	0.8	0.167	0.5	0.65
Agent 10	0.875	0.167	0.625	0.9	0.65
Agent 11	0.9583	0.375	0.625	0.5	0.15
Agent 12	0.5625	0.375	0.167	1	0.15
Agent 13	0.5625	0.375	1	0.9	0.5625
Agent 14	0.875	0.75	0.83	0.4	0.7083
Agent 15	0.4583	0.167	0.83	0.625	0.5625
Agent 16	0.9583	0.75	0.167	1	0.15
Agent 17	0.875	0.75	0.5	0.4	0.65
Agent 18	0.4583	0.67	0.167	0.5	0.15
Agent 19	0.4583	0.67	0.625	0.9	0.7083
Agent 20	0.9583	0.375	1	0.4	0.7083

As an agent-leader, to whom agent 1 should direct managerial influences to ensure that other agents follow him, based on the analysis of the obtained reflexive characteristics of agents (Table 3) in accordance with the methodology [12-14], it is advisable to choose such an agent who has the value of the reflexive characteristics of authority and competence as close as possible to 1.

In Table 3 agent 1 represents the managing center, agent 4 acts as a leader agent ($\beta_{4t} = 1$, $\gamma_{4t} = 0{,}8$), to whom managerial influences must be directed in order to provide a signal to agents inclined to imitation that this agent can be trusted in the correctness of the decisions made and, accordingly, he can be imitated. Consequently, reflexive managerial influences will be directed at him to start the mechanism of imitation among other agents.

Thus, the obtained values of the reflexive characteristics of agents in the areas of detection can be used to select a circle of agents for the realization of reflexive managerial actions to achieve the goals of enterprise management, as well as to forecast the results of decision-making by agents about the choice of alternatives using the functions of reflexive choice, the possibility of applying which are described in detail in [14].

Conclusions

To determine the values of reflexive characteristics of agents in the article it is proposed to use a complex of models developed on the basis of survey methods, the apparatus of fuzzy set theory by L. Zadeh, and neural network modeling. The determination of the values of reflexive characteristics of agents (awareness, competence, authority, propensity to imitate and decision value) is carried out by forming fuzzy sets within the framework of the theory of L. Zadeh and calculating the properties of agents according to the results of questionnaires in selected areas.

Based on the membership of agents to corresponding fuzzy sets, the Kohonen map groups agents into clusters with the aim of determination of the values of their reflexive characteristics. In this case, as a result of clustering with Kohonen maps, a potential circle of agents is revealed, on which the managing effects of the mechanism of reflexive management of herd behavior will be directed.

An important applied value of interpreting the results of SOM clustering is the possibility of obtaining both representatives of specific classes and average values of the characteristics of class representatives, which are determined by the parameters of the network neurons and represent cluster centers. The reflexive characteristics of each of the agents in the resulting clusters after processing by the neural network are proposed to be assigned the values of the parameters of the neuron that determines the cluster center. Thus, as a result of clustering the input data vectors along the directions for determining the values of the reflexive characteristics of agents, typical values of the required parameters for agents representing classes are obtained.

These values can be used within the framework of the mechanism for diagnosing the manifestations of herd behavior in enterprises, for managing the decision-making process of agents and for predicting the behavior of agents using the functions of reflexive choice.

Promising direction of research is in the development of individual diagnostic mechanisms and a system of practical recommendations for the reflexive management of herd behavior regarding managerial decisions at meetings of various levels of enterprise management, decisions on choosing suppliers and consumers of enterprise products, counteracting staff resistance to organizational changes.

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References

1. Allais, M. (1953). Le comportement de l'homme rationnel devant le risque: critique des postulats et axiomes de l'école américaine. *Econometrica, 21*(2), 503–549.

2. Kahneman, D., & Tversky, A. (1979). Prospect theory: an analysis of decisions under risk. *Econometrica, 47*(2), 263-291. https://doi.org/10.2307/1914185

3. Thaler, R. H. (2015). *Misbehaving: The Making of Behavioral Economics.* W.W. Norton & Company.

4. Yi., H., & Xiugang, Y. (2019). Managers' Overconfidence, Risk Preference, Herd Behavior and Non-efficient Investment. *Independent Journal of Management & Production, 10*(1), 56-75. https://doi.org/10.14807/ijmp.v10i1.845

5. Loxton, M., Truskett, R., Scarf, B., Sindone, L., Baldry, G., & Zhao, Y. (2020). Consumer behaviour during crises: Preliminary research on how coronavirus has manifested consumer panic buying, herd mentality, changing discretionary spending and the role of the media in influencing behaviour. *Journal of risk and financial management*, *13*(8), Article 166. https://doi.org/10.3390/jrfm13080166

6. Pavlović-Höck, N. (2022). Herd behaviour along the consumer buying decision process - experimental study in the mobile communications industry. *Digital Business, 2*(1), Article 100018. https://doi.org/10.1016/j.digbus.2021.100018

7. Fang, H., Lu, Y.-Ch., Shieh, J.C.P., & Lee, Y.-Hs. (2021). The existence and motivations of irrational loan herding and its impact on bank performance when considering different market periods. *International Review of Economics & Finance, 73*, 420-443. https://doi.org/10.1016/j.iref.2021.01.015

8. Merkulova, T., & Kononova, K. (2015). Neyrosetevoy podhod k modelirovaniyu povedeniya: analiz rezultatov eksperimenta «Obschestvennoe blago» [Neural network approach to modeling behavior: the analysis of PG game outcomes]. *Neiro-nechitki tekhnolohii modeliuvannia v ekonomitsi (Neuro-Fuzzy Modeling Techniques in Economics), 4,* 113–134. http://doi.org/10.33111/nfmte.2015.113 [in Russian]

9. Danich, V.M., & Shekhovtsova, K.V. (2013). Valiutna panika, azhiotazh ta yikh vplyv na diialnist pidpryiemstv [Currency Panic, Agiotage and their Influence on Company Activity]. *Biznes Inform (Business Inform), 6,* 8–13. https://www.business-inform.net/export_pdf/business-inform-2013-6_0-pages-8_13.pdf [in Ukrainian]

10. Solodukhin, S. V. (2017). Osnovnyie predposylky postroeniya modeley stadnoho povedeniya vo vneshney i vnutrenney srede predpriyatiy [The main prerequisites for the construction of models of herd behavior in the external and internal environment of enterprises]. *Problemy systemnoho pidkhodu v ekonomitsi (Problems of the systemic approach in economy),*

4(60), 181–186. http://www.psae-jrnl.nau.in.ua/journal/4_60_2017_ukr/26.pdf [in Russian]

11. Lepa, R. M., Okhten, A.A., & Stashkevich, I.I. (2016). Minimizatsiia oporu personalu orhanizatsiinym zminam na pidpryiemstvi [Minimizing personnel resistance to organizational changes at enterprise]. *Ekonomika promyslovosti (Economy of industry), 3*(75), 90–115. https://doi.org/10.15407/econindustry2016.03.090 [in Ukrainian]

12. Stashkevych, I., Turlakova, S., Shevchenko, O., & Derzhevetska, M. (2020). IDEF0-Technology of Modeling of Processes of Minimization the Resistance of the Personnel to Organizational Changes at the Enterprise. *WSEAS Transactions on Environment and Development*, *16*, 286-296. https://doi.org/10.37394/232015.2020.16.30

13. Turlakova, S., Vyshnevskyi, O., Lohvinenko, B., & Fomichenko, I. (2020). Role of Reflexive Characteristics of Agents in the Level of Consistency of Goals in the Group. *WSEAS Transactions on Environment and Development*, *16*, 297–304. https://doi.org/10.37394/232015.2020.16.31

14. Turlakova, S.S. (2020). *Refleksivnoe upravlenie stadnyim povedeniem na predpriyatiyah: kontseptsiya, modeli i metodyi (Reflexive management of herd behavior at enterprises: concept, models and methods)*. NAN Ukrainy, In-t ekonomiki prom-sti. [in Russian]

15. Zadeh, L.A. (2008). Is there a need for fuzzy logic? *Information Sciences*, *178*(13), 2751-2779. https://doi.org/10.1016/j.ins.2008.02.012

16. Cattell, R. B. (1988). The meaning and strategic use of factor analysis. In J. R. Nesselroade & R. B. Cattell (Eds.), *Handbook of Multivariate Experimental Psychology* (pp. 131–203). Plenum Press. https://doi.org/10.1007/978-1-4613-0893-5_4

17. McClelland, D. C. (2001). Chapter 27: Where Do We Stand on Assessing Competencies? In J. Raven, & J. Stephenson (Eds.), *Counterpoints: Vol. 166. Competence in the learning society* (pp. 479–489). Peter Lang AG. https://www.jstor.org/stable/42977810

18. Spencer, L. M., & Spencer, S. M. (2008). *Competence at Work models for superior performance*. John Wiley & Sons.

19. Hartigan, J.A., & Wong, M.A. (1979). A k-means clustering algorithm. *Journal of the Royal Statistical Society. Series C*, *28*(1), 100-108. https://doi.org/10.2307/2346830

20. Kaufman, L., & Rousseeuw, P. J. (1990). Partitioning Around the Medoids (Program PAM). In *Wiley Series in Probability and Statistics. Finding Groups in Data: An Introduction to Cluster Analysis* (pp. 68–125). John Wiley & Sons. https://doi.org/10.1002/9780470316801.ch2

21. Jolliffe, I.T. (2002). *Principal Component Analysis* (2nd ed.). Springer. https://link.springer.com/book/10.1007/b98835

22. van der Maaten, L., & Hinton, G. E. (2008). Visualizing High-Dimensional Data Using t-SNE, *Journal of Machine Learning Research, 9*, 2579-2605. https://lvdmaaten.github.io/publications/papers/JMLR_2008.pdf

23. Sokal, R., & Rohlf, F. (1962). The comparison of dendrograms by objective methods. *Taxon*, *11*, 33-40. https://doi.org/10.2307/1217208

24. Caliński, T., & Harabasz, J. (1974). A Dendrite Method for Cluster Analysis. *Communications in Statistics - Theory and Methods*, *3*, 1-27. https://doi.org/10.1080/03610927408827101

25. Schubert, E., Sander, J., Ester, M., Kriegel, H., & Xu, X. (2017). DBSCAN revisited, revisited: Why and how you should (still) use DBSCAN. *ACM Transactions on Database Systems*, *42*(3), 1-21. https://doi.org/10.1145/3068335

26. McInnes, L., & Healy, J. (2018). *UMAP: Uniform Manifold Approximation and Projection for Dimension Reduction*. arXiv. https://doi.org/10.48550/arXiv.1802.03426

27. Zhang, T., Ramakrishnan, R., & Livny, M. (1996). BIRCH: an efficient data clustering method for very large databases. In *Proceedings of the 1996 ACM SIGMOD international conference on Management of data* (pp. 103–114). ACM. https://doi.org/10.1145/233269.233324

28. Kohonen, T. (2001). *Self-Organizing Maps*. Springer–Verlag.

29. Kohonen, T. (2008). Data management by self-organizing maps. In J.M. Zurada, G.G. Yen, & J. Wang (Eds.), *Lecture Notes in Computer Science: Vol. 5050. Congress on Computational Intelligence: Research Frontiers* (pp. 309-332). Springer. https://doi.org/10.1007/978-3-540-68860-0_15

30. Kohonen, T. (2013). Essentials of the self-organizing map. *Neural Networks*, *37*, 52-65. https://doi.org/10.1016/j.neunet.2012.09.018

31. Mariño, L., & de Carvalho, F. (2022). Two weighted c-medoids batch SOM algorithms for dissimilarity data. *Information Sciences*, *607*, 603-619. https://doi.org/10.1016/j.ins.2022.06.019

32. Kobets, V., & Novak, O. (2021). EU countries clustering for the state of food security using machine learning techniques. *Neuro-Fuzzy Modeling Techniques in Economics*, *10*, 86-118. https://doi.org/10.33111/nfmte.2021.086

33. Kobets, V., & Yatsenko, V. (2019). Influence of the fourth industrial revolution on divergence and convergence of economic inequality for various countries. *Neiro-Nechitki Tekhnolohii Modelyuvannya v Ekonomitsi*

(Neuro-Fuzzy Modeling Techniques in Economics), 8, 124-146. http://doi.org/10.33111/nfmte.2019.124

34. Subasi, A. (2020). Clustering examples. In *Practical Machine Learning for Data Analysis Using Python* (pp. 465-511). Elsevier. http://doi.org/10.1016/b978-0-12-821379-7.00007-2

35. Kaski, S. (2011). Self-Organizing Maps. In C. Sammut, G.I. Webb (Eds.), *Encyclopedia of Machine Learning* (pp. 886-888). Springer. https://doi.org/10.1007/978-0-387-30164-8_746

36. Matviychuk, A., Lukianenko, O., & Miroshnychenko, I. (2019). Neuro-fuzzy model of country’s investment potential assessment. *Fuzzy economic review*, *24*(2), 65-88. https://doi.org/10.25102/fer.2019.02.04

37. Lo, Z.-P., Fujita, M., & Bavarian, B. (1991). Analysis of neighborhood interaction in Kohonen neural networks. In *6th International Parallel Processing Symposium Proceedings* (pp. 247–249). IEEE Computer Society.

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EMPLOYMENT IN THE COORDINATES OF DIGITAL ECONOMY: CURRENT TRENDS AND FORESIGHT TRAJECTORIES

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The article presents a scientific and applied argumentation of current trends and the authors' vision of foresight trajectories of employment in the coordinates of digital economy. A critical synthesis of existing scientific research has been carried out, which has shown the dynamic scaling of digital economy in global economic space with profound multi-vector shifts in employment at various levels.

The authors' hypothesis that the scale and structure of employment would change intensively in both constructive and destructive dimensions under the influence of digitalization has been suggested and proved. The nature of constructivism and destructiveness of such changes has been disclosed.

Trends in the level of employment in global coordinates, in Europe as a whole and in Ukraine have been analyzed with the use of the International Labour Organization's information resource.

It was clustered eight analyzed industries (in the field of high-tech manufacturing, high-tech services and certain export-oriented industries) using Kohonen self-organizing maps toolset, which allowed, based on a set of characteristic socio-labour and socio-economic indicators of the State Statistics Service of Ukraine for the period from

2013 to 2020, to analyze the state of development of each industry by the structure of employed and economic development, as well as to study trends in changes in state of industries in dynamics under conditions of digitalization.
The analysis of the clustering results showed that despite very serious economic challenges and real problems in most industries, 2014 and 2020 can be considered the years of rapid development of digital technologies in high-tech industries, which were accompanied by a reduction in the number of employees and a decrease in salaries. The least digital transformations mainly concerned industrial sectors during the years of economic recovery of Ukraine in the period from 2015 to 2018.
Results of the study of the impact of employment in high-tech industries and high-tech services sectors on the dynamics of gross domestic product and gross value added in the Ukrainian economy are presented. Results of forecasting these indicators with allocation of upper and lower confidence limits in a trend have been presented, which allowed to model optimistic, realistic and pessimistic scenarios of the abovementioned macroeconomic indicators development. A hypothesis regarding increase in the probability of implementing an optimistic scenario of gross domestic product and gross value-added dynamics under conditions of digitalization by optimizing the number and the structure of those employed in the high-tech segment has been proposed and proved.

Keywords: *world of work digitalization, destruction of employment, constructivism of transformations in employment, future of employment, human-centered sustainable development, economic sectors clustering, high-tech industries*

JEL Classification: C38, E24, J21, J23

Introduction

Fundamental technological, information, communication and demographic transformations of the third decade of the XXI century are causing large-scale and profound changes in economic development determinants, economic management methods, system of social division of labour and work activities organization, and value priorities of economically active people. The output of these transformations would be fundamental changes in all spheres of economic, social and public existence; a new format of the world of work; a new network society.

An unbiased analysis of the new socio-economic reality demonstrates that perhaps the most significant changes in the life of an economically active person in the modern digital age are associated with their inclusion in socially organized labour, with employment in its broadest sense.

All these changes remain systematically unexplored and unexplained from a scientific point of view, both in terms of their nature and especially their social consequences for a digital age person. The following questions remain unanswered: What will be the human dimension of the digital economy? What will be the balance of benefits and losses for society during "humanless" economy development? How to adapt to global changes that are becoming a rule rather than an exception? What toolset should be used for forecasting changes in the world of work and employment?

We have to acknowledge that the stage of describing changes, stating the general, obvious, and producing fragmentary constructs has long since passed. A new theory of social and labour development should be formed with the use of modern scientific potential and an interdisciplinary approach, which would explain the true nature of the world of work and the world of people in the digital age, their resources, competitive advantages and, at the same time, "failures", new mechanisms, tools of functioning and regulation.

Particularly evident are the dynamics of global multi-vector transformations, instability, unpredictability, and asymmetries in their various manifestations, which are illustrated by the example of employment sector, which is centered on an economically active person with accumulated labour potential, motivations, and values of working life. Until recently, academic discussions on social and labour issues in general and employment issues in particular have focused on market uncertainty and government regulation mechanisms [1], multi-vector trends in precarious work with a focus on self-employment [2-6], threats and prospects for employees with different skill levels [7-9], impact of technical and technological transformations on the supply and demand for labour services [10-12]. However, realities of today and horizons of the future require shifting scientific discussions and scientific support for the development of the social and labour sphere from traditional problematics to issues of a different order, the key among which is prediction of future employment trajectories.

The article offers readers an argumentation of the authors' vision of the employment model in the context of digital economy challenges.

One can find many, often diametrically opposed assessments in socio-economic and philosophical literature today – from statements about the emergence of almost communism in the world of work and employment following development of the digital economy [13] to apocalyptic predictions of a "society without work" in the near future [14, 15]. In their numerous previous publications [16-19] the authors of the article, using the language of scientific principles, concepts, and mental schemes, tried to outline their own position on where the modern world of work and the world of people are actually drifting, what is the nature of changes, and how to use the possibilities of radical adaptability to conditions of upcoming activities of daily living.

This article is a result of recent scientific research with the use of modern methodology and toolset for scientific knowledge of phenomena and processes in the field of social and labour development, including the use of economic and mathematical modelling potential in the field of employment.

The old-new hypotheses advocated by the authors include predictions and strong arguments in favour of the fact that many publications contain overestimates regarding destructive impact of digital technologies on employment scale and structure; a number of factors and circumstances that produce new forms and types of employment, generate transformational processes that remain latent, unacknowledged and unexplained from a scientific point of view, are left unaddressed.

Foresight research of social and labour dimension of digital economy does not sufficiently reflect and take into account such phenomena and processes of modern era as changes in quantitative and qualitative demographic characteristics of the population with reference to the needs and prospects of local labour markets; new configuration and trends in development of non-standard forms of employment; high probability of massive introduction of new working time models, and, consequently, neglect of fundamental changes in the system of “work – leisure”, “working time – non-working time”, “standard employment – non-standard employment”; emergence of new areas of economic activity capable of producing in the near future such goods and services that society is still unaware of; preservation of types of economic activity that will not be significantly affected by digitalization, given the economic and social inexpediency of introducing breakthrough digital technologies; deliberate restrictions on introduction of the latest technologies on the part of international organizations and national governments, given the unpredictable consequences for a healthy, fulfilling lifestyle and positive socio-economic dynamics; changes in the structure and hierarchy of social values, emergence of a new, post-industrial, post-information motivation for labour activity.

Thus, every day scientific community is facing new tasks under the influence of challenges and threats of digital age. The question is not about the traditional – the affirmation of the “end of history”, “end of the world”, “end of work”, but about the need to find what is really important for sustainable human-centred development.

The relevant research was conducted and a scientific publication based on its results was prepared within the framework of the growth of human-centred knowledge and the search for answers to questions: How to build a society not without work and employment, but a human-centred one, with employment as a social value? How to form economic and social culture of human-centered development?

Theoretical basis

In the first decades of the XXI century, the global world is undergoing fundamental digital transformations. Digital economy is scaling dynamically in global economic space, causing profound multi-vector shifts in various segments, areas of activity, and industries. One of such vectors is fundamental changes in the field of labour activity, imminence of the onset of the “end of work” in its classical sense.

Industry 4.0's breakthrough technologies enable numerous operational functions to be performed in real time without human intervention, generate and process an unprecedented amount of information [20].

Employment mechanisms are being modified under the influence of digital platforms development that create prerequisites for interaction between employers and employees in online environment [21]. According to European Jobs Monitor 2016, routine and codified jobs may be automated and employment in such sectors is expected to decline. However, some professions, despite requiring low skills, cannot be easily automated, and demand for such low-skilled labour remains. At the same time, an increase in relative demand for high proficiency and specialized skills is expected, and, accordingly, in remuneration of such employees [22].

At the same time, new jobs are being created and will continue to be created. However, employees who lost their jobs during transition may be least prepared to take advantage of new employment opportunities. Professional competences in demand in the labour market nowadays will not correspond to the jobs of tomorrow, and acquired and improved competences are rapidly becoming outdated. As a result, future generations of employees will have to acquire digital competences at an early age and learn throughout their lives [23].

Introduction of the latest technological achievements — artificial intelligence, computerization, automation, robotics — displaces people from operational activities and leads to elimination of a significant share of traditional jobs. Findings of Chinese researchers confirm that transition to the future of the world of work will be accompanied by disruptive consequences for labour markets, and ensuring decent work will become an even more challenging task [24].

Scholars have expressed concerns that further technological development will result in machines being able to successfully perform numerous tasks, and automation will lead to a huge reduction in jobs. At the same time, it is argued which jobs computers can effectively perform independently and in which ones they can only complement human labour. The "risk group" includes jobs that involve standard physical operations that are repeated periodically in a stable environment, and cognitive activities that are subject to codification. In areas of abstract decision-making, where the ability to create and persuade is required, computers are more likely to act as assistants to highly skilled professionals [25].

Capabilities of the latest technologies, which create new challenges for the labour market, are one of the most important factors in development of the employment sector, supply and demand of labour force, and professional structure of the workforce [10].

Fundamental changes in employment conditions and in the balance of competences supply and demand have occurred and continue to occur. Many jobs and career trajectories associated with certain types of activities have become a thing of the past or have been significantly reduced [26].

According to research by McKinsey consulting company, about 30% of tasks in 60% of professions can be computerized [27].

Consequences of digitalization, as proven by scientific research results, are not exclusively negative or exclusively positive. Structural effects are growing gradually and unevenly in different areas of economic activity. Certain professions may be simultaneously exposed to transformational risks of different levels [28].

Existing studies indicate that potential for technological substitution varies significantly across different sectors of economy, and the risk of automation for a particular industry varies considerably across countries [29].

There are intense discussions regarding prospects of possible elimination of jobs as a result of automation and spread of artificial intelligence technologies. Long-term value shifts show that work is losing its importance, and the need for employment is becoming less and less influential in young people's decisions to pursue higher education. The concept of an unconditional basic income as a response to reduction in jobs has become one of the most pressing issues [15]. At one pole of scientific and practical discourse is fear that as artificial intelligence improves, it will displace employees, creating an ever-growing group of unemployed people who cannot compete economically with machines. At the other pole of debate is belief that artificial intelligence will become the best working mechanism the world has ever seen; that new AI applications, combined with human collaboration, could increase employment worldwide by at least 10% [30].

Another vector of digitalization of economy in social and labour space is formation of digital employment, which in its most general sense is an economic activity carried out at a stationary or remote workplace with the use of digital technologies and creation of an information product (provision of an information service).

The essence of digital employment is revealed through the following distinctive features:

1) technical and technological basis of labour organization is created by digital technologies;

2) result of labour is a digital product or service;

3) labour process is carried out through digitalization;

4) digital accounting and financial programs are used to pay for created digital product (provided digital service);

5) communications between employer and employees are established and implemented through online platforms.

The subject of digital employment is an economically active person with digital competences – a “digital employee”. In interpreting the concept of a “digital employee”, researchers focus on performance of labour functions using information, computer and other breakthrough technologies of Industry 4.0. At the same time, employment agreement (contract) with employer is concluded digitally, interaction with team members takes place through online platforms, and remuneration for services rendered is made through digital accounting and financial system.

Theory proves, and practice convinces, that digital employment is heterogeneous in terms of the content of labour processes and labour results, so it is classified according to various criteria, including specifics of products (services), complexity of labour functions, innovative and intellectual level of obtained result. According to N. Azmuk, the main classification feature of digital employment should be considered the innovative and intellectual level of obtained result, by which digital employment is proposed to be divided into basic and smart employment [31]. Basic digital employment involves performing any work digitally using digital tools in accordance with a given technology (automated translations, blogging, software testing, website administration, etc.). The result of basic digital employment is a digital service provided in accordance with pre-established regulations, which is not unique, has no innovative content and can be reproduced for a certain range of consumers. The second level of digital employment in the world practice is denoted by the abbreviation SMART (from the terms Specific, Measurable, Attainable, Relevant, Time-bound), which is widely used in the field of project management [32]. Digital smart employment results in developing a new digital product or improving an existing one. Thus, smart employment is to be considered as aimed at effective solution of tasks related to production of innovations [31].

Digital employment most often takes forms of flexible employment, which have their own strengths and weaknesses. Strengths primarily include the ability to independently arrange work and rest schedules, as well as considerable freedom in choosing tasks and orders. As for weaknesses, social protection is often not guaranteed; there is no control over work results; and there is a high level of uncertainty. A high level of professionalism is a kind of “protection” for “digital employees”, but it does not compensate for the lack of guarantees of proper social protection [33].

Digital employment is inherent in all areas of economic activity without exception, but it is mostly concentrated in high-tech segments of economy, which provides a certain effect for macroeconomic dynamics.

Research methodology

The research’s methodological platform consists of systemic and interdisciplinary approaches, which contributed to the argumentation of new opportunities and new challenges, risks and threats in the field of employment under conditions of economy digitalization.

The central point of this article is the authors’ hypothesis, which is formulated as follows: labour practices, scale and structure of employment will change intensively under the influence of digitalization. These changes can be viewed in at least two dimensions – constructive and destructive, which are transformational in nature. Both the first (constructive) and the second (destructive) dimensions of transformational changes in the employment sector can be clearly traced on the example of occupational groups. Authors of the article are supporters of occupational classification which includes four enlarged groups in terms of effect of digitalization.

The extreme poles of these groups are “rising stars” (professions that are in demand in digitalization era and this demand tends to increase) and “dying professions” (their functions are being taken over by digitalization, radically reducing the need for human resources) [28]. The nature of transformational changes in employment sector, according to the authors’ hypothesis, is not only of digital, information and communication origin. Constructive and destructive effects of digitalization can be enhanced, reduced, or completely eliminated depending on a number of factors that directly or indirectly affect the sectoral structure of employment. However, it is not unreasonable to assume that professions in demand during digitalization era (“rising stars”) are mostly concentrated in high-tech segment, where both creation of digital products and their common usage take place.

In order to allocate groups of such types of activities, it is suggested to apply a cluster analysis methodology, which allows identifying common properties and patterns of trends in the development of areas of economic activity and industries under conditions of digitalization by a set of socio-labour and socio-economic development indicators.

Results

Study of key factors that affect employment structure in the labour market

The world practice of scientific study of labour market and employment parameters in the near and distant future justifiably considers the scale and professional dimension of employment, constructive and destructive changes in social and labour relations under the influence of digitalization in its broadest meaning as the basis for foresight analysis. The authors of this article follow these positions and logically continue their research of a prognostic nature, which covers the forecasting of the world of work and employment in the short and long term [34] and takes into account experience of countries that have achieved the greatest progress in digitalization. Our research confirms that intensive penetration of digitalization into all areas of economic activity and transfer of business processes into a digital environment is causing a fundamental reformatting of employment scale and structure, as well as professional dimension of digital economy.

We are convinced that the "relationship" between digital technologies, other technical and technological innovations of the first half of the XXI century and society remains complex and often incomprehensible in terms of the consequences of potential interaction. And this applies not only to individual companies, regions, and countries, but has become a global trend.

The International Labour Organization's [35] estimates of potential changes in the scale of employment caused by technological and demographic factors are demonstrated in Table 1.

Our principled position has always been and remains that demographic shifts are, in practice, one of the reasons for fundamental changes in the world of work and employment and formation of a new socio-economic reality. The most significant trends of demographic nature that have a global impact are as follows

- decrease in population growth rates in most countries of the world;
- increase in the average age of population;
- decrease in the share of children and adolescents in population;
- increase in the proportion of older people;
- increase in the demographic burden on working-age population;
- decrease in the share of working-age population;
- permanent intensification of migration processes and their increasing impact on demographic changes indicators;
- women's transition from household management to active participation in social production.

Table 1

ESTIMATES OF FUTURE CHANGES IN LABOUR MARKETS

Factor	Impact estimates
Technology	Automation that leads to job replacement threatens 47% of employees in the USA [36]
	ASEAN-5: automation will threaten 56% of jobs in the next 20 years [29]
	While proven technologies can fully automate less than 5% of all activities, in approximately 60% of all activities, at least 30% of operations performed in them are subject to automation [37]
	On average, 9% of jobs in OECD countries are at high risk of automation. A significant proportion of jobs (50% to 70%) will not be fully replaced, but automation will affect a large proportion of operations, changing the very way they are performed [38]
	Two-thirds of all jobs in developing countries could be automated [39]
	Almost 50% of companies predict that by 2022, automation will cause a certain reduction in the number of their full-time employees [40]
Demographic changes	It is projected that by 2050, the overall dependency ratio (the number of people aged under 14 and over 65 for every 100 people aged 15 to 64) will increase drastically in Europe (by 24,8 percentage points) and North America (by 14.4 percentage points) and moderately in Asia (by 8.5 percentage points), Oceania (by 6.8 percentage points), and Latin America and the Caribbean (by 7.6 percentage points). It is projected that the overall dependency ratio in Africa will decline by 18.7 percentage points and that half of its population will consist of young people (from birth to 24 years). In all other regions, the population will be ageing [41]

Mentioned trends are shaping new parameters of labour market and require active social and labour policy on the part of the state. An impartial analysis convinces that one of the paradoxes of the present day is the aggravation of human resources problem, especially among younger and middle-aged groups, against the background of absence or lesser importance of demographic issues in relation to the population as a whole. Quantitative and qualitative parameters of the population as a whole and quantitative and qualitative parameter of the working-age population, especially of younger age groups, have different, often diametrically opposite tendencies of formation and development. As shown in Fig. 1, built on the basis of data from International Labour Organization [42], the level of population participation in global labour force, in the EU27, and in Ukraine is gaining new momentum in positive dynamics after a noticeable "slump" in 2020. In Europe, the downward trend of this indicator, according to forecasts for 2021-2023, is typical only for Eastern European countries.

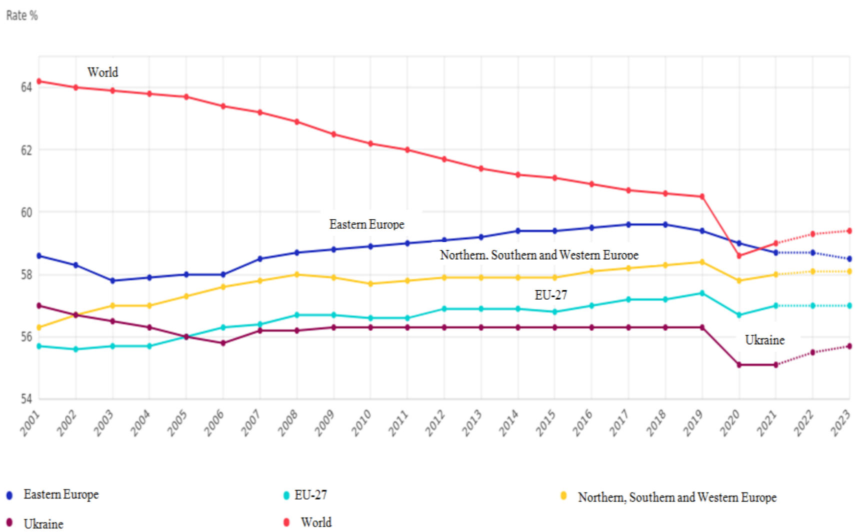

Fig. 1. Level of participation in labour force
(labour force as a percentage of the working age population)

As in Fig. 1, as in Figs. 2, 3, indicators include both real and conditional data for 1991-2021, as well as forecasts for 2022-23 from source [42]. Estimates may differ from official national sources.

Despite the existing pessimistic employment forecasts, the level of employment in global coordinates, in Europe as a whole, and in Ukraine will not have a downward dynamic in the near future (Fig. 2), and unemployment rates will be declining in foreseeable time (Fig. 3), delaying the predicted "unemployed future".

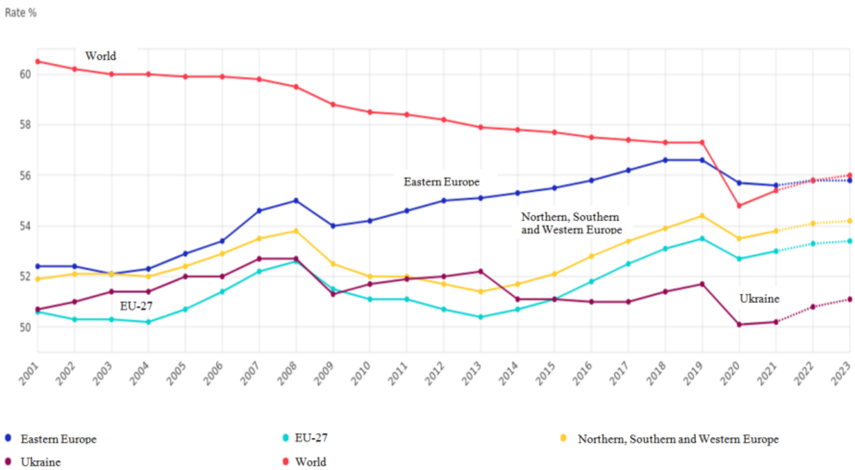

Fig. 2. Level of employment (number of employed as a percentage of the total working age population)

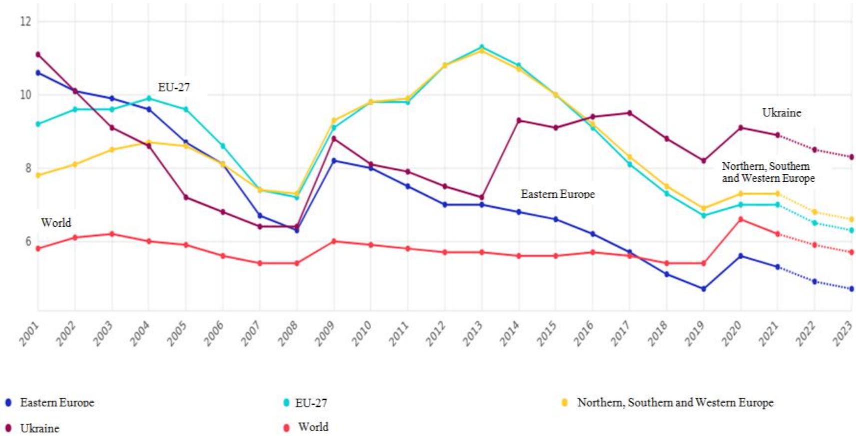

Fig. 3. Level of unemployment (number of unemployed as a percentage of the labour force)

Transformational consequences of digitalization for professional employment, according to our methodological basis, can be reduced to two enlarged groups: constructive and destructive. Constructive effects of digitalization are manifested primarily in emergence of new goods and services; replenishment of the world of professions with new ones, often exotic, integrated, interdisciplinary professional tasks; creation of “employment of the future”. Destructive effects of digitalization are manifested in replacement of employees as a result of their functions’ transfer to machines and digital technologies; an intense decline in demand for competencies that were still dominant yesterday; formation of a “dying professions” layer.

By focusing on development of theoretical construct of the employment XXI model as a response to the changing world of work and employment under the influence of the ultra-scale, ultra-deep and ultra-controversial process of digitalization, we have conducted a preliminary analysis of scientific achievements in this area from different schools of thought. This analysis demonstrated the dominance of studies that focus on destructive effects. At the same time, there is still insufficient research on the phenomena, trends, dominants, and effects under which the format and nature of professional activity are changing, labour productivity is increasing, but there is no threat of complete replacement of human labour by machines and digital technologies, or constructive effects outweigh destructive ones.

Our preliminary research suggests that the impact of digitalization on the scale and structure of professional activity cannot be considered either purely destructive or exclusively constructive [43]. The authors’ approach to substantiating the employment-XXI model based on expected shifts in professional activity is close to the one advocated by American researchers F. Fossen and A. Sorgner [28]. What our approaches have in common is the identification of enlarged groups of professions and vectors of change in the structure of employment and its professional dimension in the context of global digitalization. The differences lie in the authors’ rejection of their American colleagues’ methodological basis, which divides digitalization effects into destructive (negative) and transformative ones. According to our assumption, as already mentioned above, both positive and negative effects of digitalization are of transformational origin. The second fundamental difference between the authors’ concept of the professional employment model and the American researchers' construct is a broader view on manifestation of transformational effects, which are not limited to the emergence of new and disappearance of existing professions, but include a number of other components (effects) – emergence of new areas and types of professional activity, increased productivity; "emasculation of economy" and disappearance of professions, which borders and coexists with new "rising economies" and "rising stars" professions; an in-depth view of professions development dominants that are conditionally located in the "territory of machines", on the one hand, and "territory of humans", on the other. A schematic of the authors' concept of transformational effects of digitalization on the world of labour and employment is shown in Fig. 4.

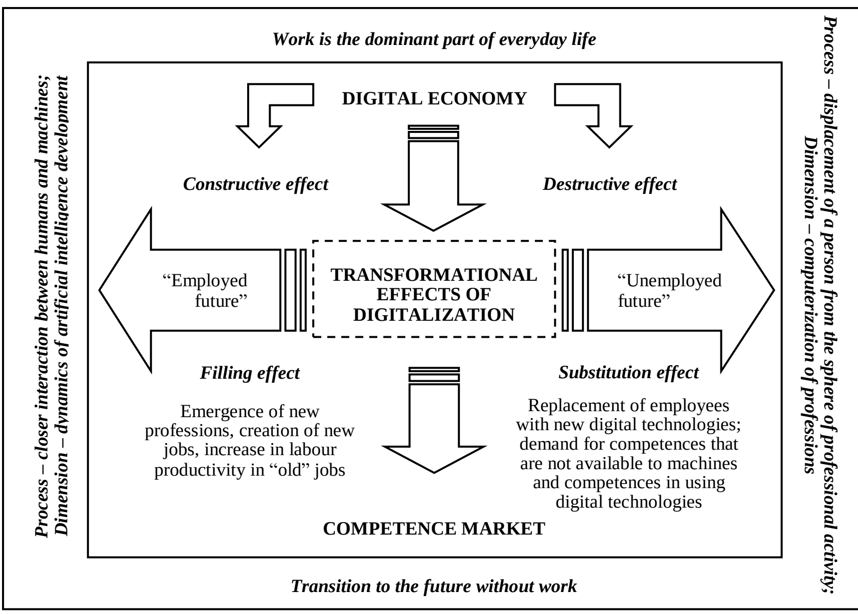

Fig. 4. Schematic of the authors' concept of transformational effects of digitalization on the world of labour and employment

We emphasize that both positive (constructive) and negative (destructive) consequences of digitalization, which are intensifying in all spheres of economic and social life, arise in the process of multi-vector, large-scale, profound transformations. Therefore, both the former and the latter are transformational. At the same time, some of them are predominantly of a destructive, “emasculating” nature, while others are of a creative, producing nature.

We strongly believe that one of the defining trends in digital economy development should be dynamic growth of high-tech sector, where employment optimization will contribute to improvement of macroeconomic situation both globally and nationally.

Research on common properties of scopes of activities under conditions of digitalization

In order to verify validity and substantiate the authors’ hypothesis mentioned at the beginning of the article, that labor practices, the scale and structure of employment will change intensively under the influence of digitalization, which can be monitored on the example of groups of professions, we will examine similar changes over a number of years in a number of high-tech industries (Manufacture of basic pharmaceutical products and pharmaceuticals; Manufacture of computers, electronic and optical products; Manufacture of electrical equipment), high-tech services sector (Information and telecommunications; Research and development), and export-oriented industries (Manufacture of food, beverages and tobacco products; Metallurgical production, manufacture of fabricated metal products (except machinery and equipment); Manufacture of chemicals and chemical products).

As mentioned above, the authors of the article are supporters of the classification of professions in which there are consolidated groups from the point of view of the effect of digitalization, when there are professions that are in demand by “digit” and this demand tends to increase, and professions whose functions are taken over by “digit”, radically reducing the need for human resources. These tendencies can be studied by separating groups of professions according to a set of characteristic indicators over a sufficiently long period of time under conditions of digitalization of economy, for which it was decided to apply the cluster analysis methodology.

Given the objectives of this study, in order to cluster types of activities under conditions of digitalization in terms of the number of employed, the structure of employees, the level of salaries and economic development of high-tech segment and export-oriented industries, Kohonen self-organizing maps toolkit was used [44], which, in addition to solving the tasks of reducing dimensionality in complex data sets and forming homogeneous groups of studied objects, provide an opportunity for visual analysis of clustering results [45]. This makes it possible to analyze the state of development of each industry in terms of the structure of employment and economic development among other sectors of economy, as well as to study trends in the state of industry in the dynamics of digitalization.

In order to conduct such a study, a database for the period from 2013 to 2020 was compiled using data from the State Statistics Service of Ukraine [46] for a set of indicators: Average number of full-time employees, '000 people; The share of the average number of full-time employees in the average number of full-time employees in the economy of Ukraine as a whole, %; Average number of non-registered employees (attracted on the terms of civil law contracts and external part-time workers), '000 people; Share of the number of non-registered employees in the total average number of employees, %; Output (in consumer prices), UAH million; Gross profit, mixed income (in consumer prices), UAH million; Average monthly salary of full-time employees (nominal), UAH; The ratio of the average monthly salary of full-time employees to the average monthly salary in the Ukrainian economy as a whole, %; Average monthly salary of full-time employees (real – adjusted by consumer price index), UAH; Remuneration of salaried employees, UAH million; Gross value added (in consumer prices), UAH million; Gross domestic product (in consumer prices), UAH million (see Table 2).

The left-hand column of Table 2 shows abbreviated industries: Pharmacy – Manufacture of basic pharmaceutical products and pharmaceuticals; Computers – Manufacture of computers, electronic and optical products; Electrics – Manufacture of electrical equipment; Food – Manufacture of food, beverages and tobacco products; Metallurgy – Metallurgical production, manufacture of fabricated metal products (except machinery and equipment); Chemicals – Manufacture of chemicals and chemical products; Telecom –

Table 2

DATABASE WITH INDICATORS OF LABOUR MARKET AND ECONOMIC DEVELOPMENT OF HIGH-TECH AND EXPORT-ORIENTED INDUSTRIES, HIGH-TECH SERVICES

Industry	Year	Average number of full-time employees, thousand people	The share of the average number of full-time employees in the average number of full-time employees in the economy of Ukraine as a whole, %	Average number of non-registered employees (attracted on the terms of civil law contracts and external part-time workers), thousand people	Share of the number of non-registered employees in the total average number of employees, %	Output (in consumer prices), UAH mln	Gross profit, mixed income (in consumer prices), UAH mln	Average monthly salary of full-time employees (nominal), UAH	The ratio of the average monthly salary of full-time employees to the average monthly salary in the Ukrainian economy as a whole, %	Average monthly salary of full-time employees (real – adjusted by consumer price index), UAH	Remuneration of salaried employees, UAH mln	Gross value added (in consumer prices), UAH mln	Gross domestic product (in consumer prices), UAH mln
1	2	3	4	5	6	7	8	9	10	11	12	13	14
Pharmacy	2013	21	0,23	1,8	7,56	34020	1069	5422	166	5438	2060	3223	8341
Pharmacy	2014	22	0,25	1,8	7,56	41105	2081	6219	178,7	5548	2976	5163	11104
Pharmacy	2015	21	0,26	1,5	6,67	53164	3428	8254	196,8	5551	3453	7002	15988
Pharmacy	2016	22	0,28	1,5	6,38	73330	5367	11028	212,8	9682	3725	9099	20134
Pharmacy	2017	23	0,3	1,3	5,65	79705	5757	13846	194,9	12103	4813	10638	24654
Pharmacy	2018	24	0,31	1,3	5,14	91895	5656	16754	189	15259	6925	12649	30137
Pharmacy	2019	24	0,32	1,2	4,76	113379	6019	19511	185,9	18743	8140	14236	32557
Pharmacy	2020	25	0,34	1,6	6,4	123953	6157	21138	182,4	20131	8824	15048	35499
Computers	2013	45	0,46	2,2	4,66	21353	355	3086	94	3095	1802	2217	5667
Computers	2014	33	0,37	2	5,71	24709	461	3211	92,3	2864	1878	2396	6147
Computers	2015	30	0,37	1,6	5,06	28875	331	4619	110,1	3106	2076	2457	8053
Computers	2016	31	0,39	1,8	5,49	43251	924	6787	130,9	5959	3002	3962	10231

1	2	3	4	5	6	7	8	9	10	11	12	13	14
Computers	2017	27	0,35	1,4	5,19	53277	349	9000	126,7	7867	4018	4403	16602
Computers	2018	28	0,37	1,6	5,4	59475	886	10640	120	9690	4615	5541	16986
Computers	2019	26	0,35	1,4	5,11	63835	910	12509	119,2	12016	5188	6143	18038
Computers	2020	24	0,33	1,2	5,38	62034	237	13275	114,5	12643	3972	4246	16551
Electrics	2013	61	0,6	2,1	3,49	36001	1392	3026	92,2	3035	4947	6508	9331
Electrics	2014	61	0,68	2,2	3,48	39119	1536	3159	90,8	2818	5326	6992	10275
Electrics	2015	53	0,66	2,1	3,81	42468	3056	3870	92,3	2603	4228	7424	12062
Electrics	2016	49	0,62	2,3	4,48	49936	4209	4803	92,67	4217	4336	8617	13681
Electrics	2017	50	0,65	1,9	3,8	64918	4757	6840	96,3	5979	5870	10702	21313
Electrics	2018	50	0,65	1,8	3,48	80406	5736	8731	98,5	7952	8218	14039	25236
Electrics	2019	45	0,61	1,6	3,43	82011	5460	10153	96,7	9753	7984	13531	24494
Electrics	2020	42	0,57	1,5	3,57	78367	3050	10531	90,9	10030	8122	11237	22358
Food	2013	349	3,59	17	4,64	472178	17770	3117	94,97	3101	26999	46070	99476
Food	2014	323	3,61	16,3	4,8	516564	26026	3337	95,89	2672	29204	56979	120394
Food	2015	290	3,6	17,8	5,78	643639	39091	4184	99,74	2920	33233	74263	165391
Food	2016	282	3,58	16,1	5,4	780383	56549	5182	99,98	4610	33376	90862	216988
Food	2017	280	3,65	13	4,44	937992	58370	6756	95,1	5942	46236	105329	276448
Food	2018	275	3,59	10,5	3,68	1040862	55321	8338	94,06	7594	56125	110624	305533
Food	2019	293	3,94	9,3	3,08	1114340	55845	9986	95,13	9593	64475	119223	320187
Food	2020	286	3,89	8,2	2,79	1266165	71244	10761	92,84	10249	72335	142919	392967
Metallurgy	2013	310	3,19	7,5	2,36	220420	2620	4150	126,45	4129	19182	23346	25451
Metallurgy	2014	272	3,04	6	2,16	260549	15562	4682	134,54	3749	23075	40249	42756
Metallurgy	2015	244	3,03	5,5	2,2	329444	19356	5645	134,56	3939	24864	45859	50792
Metallurgy	2016	218	2,77	6,1	2,72	396267	30015	6717	129,6	5976	25157	56028	62114
Metallurgy	2017	207	2,7	5,4	2,54	510182	37163	8423	118,57	7408	33700	71775	77514
Metallurgy	2018	190	2,48	5,1	2,61	602583	44521	11022	124,33	10038	40318	85797	92747

1	2	3	4	5	6	7	8	9	10	11	12	13	14
Metallurgy	2019	193	2,59	4	2,03	559796	35871	13451	128,14	12921	41304	78068	85283
Metallurgy	2020	185	2,52	3,7	1,96	504186	29549	13926	120,14	13263	40167	70408	76831
Chemicals	2013	78	0,8	2,5	3,11	83229	-1089	3640	110,91	3622	6399	5672	10870
Chemicals	2014	74	0,83	2,5	3,27	84739	-283	3971	114,11	3179	5800	5844	11359
Chemicals	2015	62	0,77	2,2	3,43	119069	1221	4988	118,9	3481	6606	8232	20099
Chemicals	2016	60	0,76	2,3	3,69	123543	1455	5932	114,45	5278	6142	7755	19153
Chemicals	2017	56	0,73	2,6	4,44	138922	623	7552	106,31	6642	7830	8602	23337
Chemicals	2018	56	0,73	1,6	2,78	161577	1863	8796	99,22	8011	8192	10210	26538
Chemicals	2019	54	0,73	1,4	2,53	166060	655	11340	108,03	10893	9051	9878	27128
Chemicals	2020	56	0,76	1,4	2,44	155179	554	12363	106,66	11774	9187	9885	26704
Telecom	2013	184	1,81	16,4	8,18	97499	23616	4599	140,9	4613	23924	48372	54887
Telecom	2014	157	1,75	14,6	8,51	105116	26952	5176	148,7	4617	24075	52724	58335
Telecom	2015	134	1,66	12,6	8,59	149296	40940	7111	169,5	4782	26268	72596	79669
Telecom	2016	122	1,55	15,2	11,08	191516	55848	9530	183,9	8367	29621	89268	97898
Telecom	2017	119	1,55	11,7	9,83	235845	67641	12018	169,2	10505	37074	110296	120482
Telecom	2018	118	1,54	13,1	8,95	299861	84269	14276	161	13002	47536	138828	151621
Telecom	2019	112	1,51	14,4	11,39	384771	109556	17543	167,1	16852	64193	182667	195928
Telecom	2020	106	1,44	8,7	8,21	413907	137705	19888	171,6	16050	69050	209394	222374
R&D	2013	115	1,13	11,5	9,09	17149	3895	4024	123,2	3767	7524	11508	…
R&D	2014	104	1,16	9,6	8,45	17968	4935	4268	122,6	4036	7624	12626	…
R&D	2015	97	1,2	10,5	9,77	22261	6499	4972	118,5	3807	6959	13492	14299
R&D	2016	91	1,16	9,6	9,54	21341	6089	6119	118,1	3344	7013	13152	13658
R&D	2017	87	1,13	7,8	8,97	24109	5944	8212	115,6	5372	10560	16546	17287
R&D	2018	93	1,21	8,7	8,55	32475	8193	10259	115,7	9343	14199	22367	23990
R&D	2019	79	1,06	8,3	9,51	35508	5965	11649	111	11190	12822	18698	20200
R&D	2020	78	1,06	7,6	9,74	36668	7921	12882	111,1	12268	13167	19541	20861

Information and telecommunications, R&D – Research and development. Abbreviations were introduced not only to avoid crowding Table 2, but also to simplify the presentation of objects on Kohonen maps in modelling and subsequent analysis of clustering results.

Deductor Studio Academic software package was used to construct self-organizing maps in this study. The map inputs are vectors of 12 values for the number of employees and their professional structure, level of salaries, and economic development of the analyzed 8 industries in 2013-2020, as shown in Table 2. Only for the "Research and development" industry the data was presented for 2015-2020 period, since for the two previous years in [47] the Gross domestic product (in consumer prices) indicator is given for the type of economic activity "Professional, scientific and technical activities" in general, without separating "Research and development" industry, as can be seen in Table 2.

This resulted in the fully expected uninformative result of clustering – industries were separately distributed into seven clusters: the zero cluster (the central upper part of the Kohonen map in Fig. 5, which can be identified by the color scale in the lower part of the figure) is completely occupied by only one industry – Research and Development (R&D); the first cluster (in the upper left corner) is completely occupied by observations of the Pharmacy industry; the second cluster (lower right corner in Fig. 5) is occupied by the Food industry; the third and sixth clusters, which occupy the upper right part of the map, were assigned to Telecom industry (whereby the last 3 years of industry observations – from 2018 to 2020 – were separated in the corner sixth cluster); the fourth cluster in the middle bottom part of the SOM is occupied by Metallurgy industry; the fifth, largest cluster in the left bottom part of the SOM contains three manufacturing industries at once – Computers, Electrics i Chemicals (whereby Chemicals industry is grouped in the right part of this cluster, closer to the other two export-oriented industries – Food and Metallurgy).

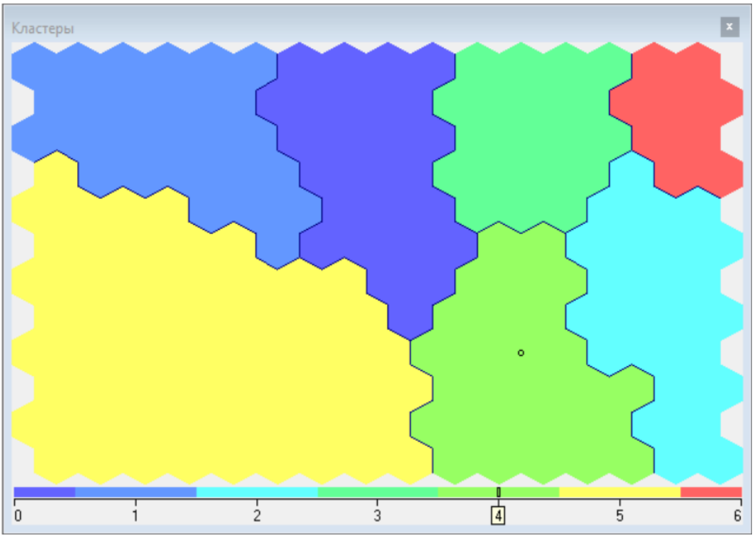

Fig. 5. The result of clustering high-tech and certain export-oriented sectors of Ukraine's economy based on indicators of their economic development, number of employees, salary and structure of employees

Such a homogeneous result of clustering by industry is due to the fact that industries are very different from each other primarily in terms of economic development (Output (in consumer prices), UAH million; Gross profit, mixed income (in consumer prices), UAH million; Remuneration of salaried employees, UAH million; Gross value added (in consumer prices), UAH million; Gross domestic product (in consumer prices), UAH million and to a lesser extent, although still significantly, from the indicators of the number and structure of employees (Average number of full-time employees, '000 people; The share of the average number of full-time employees in the average number of full-time employees in the economy of Ukraine as a whole, %; Average number of non-registered employees (attracted on the terms of civil law contracts and external part-time workers), '000 people), which can be seen both in Table 2 and in Fig. 6, which shows heat maps of the distribution of values for each of the 12 indicators.

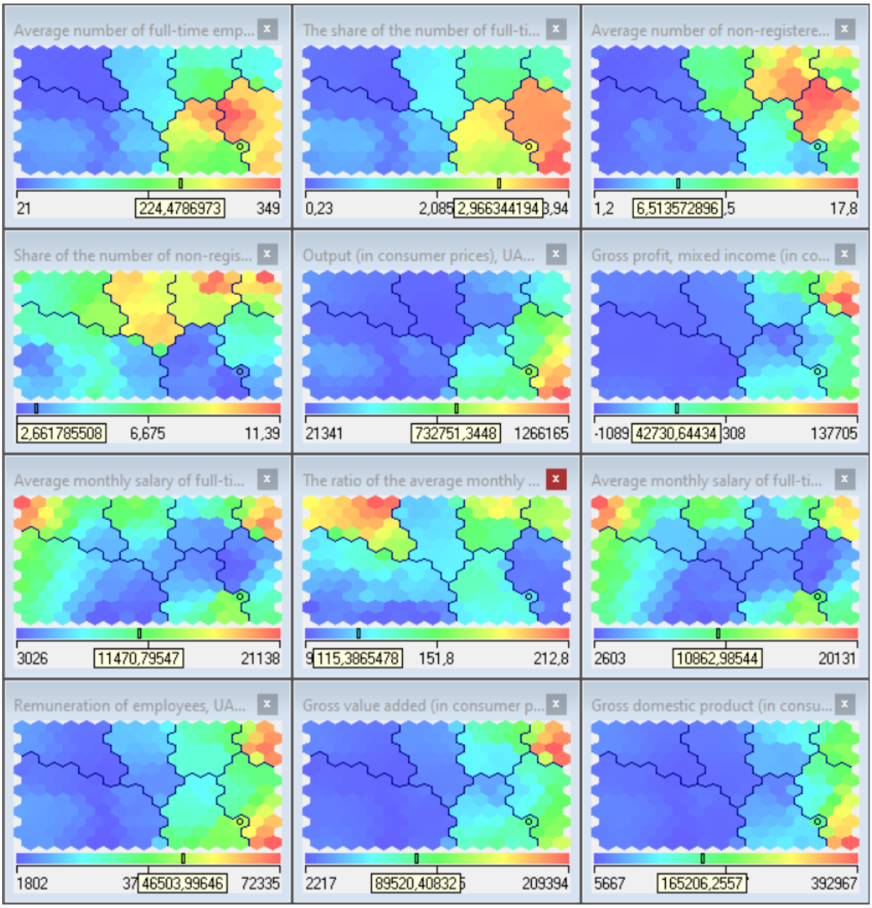

Fig. 6. Indicators values distribution on the Kohonen map

Attention should be paid to the following property of the Kohonen self-organizing map: similar investigated objects (in this case, observations by year for individual industries) are grouped together, and objects with the greatest differences are located at the maximum distance from each other (in opposite corners of the map). This can be seen in Fig. 6, where within each individual cluster, each indicator demonstrates fairly homogeneous values, and low and high values of almost all indicators are located in the diagonal corners of Kohonen map.

Thus, for example, low values of indicators Average number of full-time employees, Share of average number of full-time employees in the average number of full-time employees in the economy as a whole, and gross domestic product (in consumer prices) are concentrated in the upper left corner of the SOM, while their high values are located opposite, in the lower right corner. And for indicators gross profit, mixed income (in consumer prices) and gross value added (in consumer prices), their low values are grouped in the lower left cluster, and high values are grouped in the upper right cluster. A similar situation is observed for other indicators.

Therefore, in terms of profitability, organizations in high-tech services sector (Research and development and, especially, Information and telecommunications) significantly outperform those in high-tech manufacturing (Manufacture of computers, electronic and optical products, Manufacture of electrical equipment and Manufacture of chemicals and chemical products). The same significant advantage is observed in the level of salary (Average monthly salary of full-time employees (nominal and real) and Remuneration of salaried employees) and in The share of the number of non-registered employees in the total average number of employees.

It is clear that such a distribution characterizes not so much the specifics of the development of the studied industries' labour market under conditions of digitalization as the general patterns of socio-economic and macroeconomic nature inherent in each individual industry. Moreover, in order to reduce excessive influence of certain indicators, there is no need to standardize or normalize them, as this will not change anything fundamentally – the differences between the values of indicators in different industries are too great. Thus, in order to be able to study the dynamics of industries development in comparative terms, it is necessary to deviate from absolute values of indicators and form a set of relative predictors.

Identifying scopes of activities development patterns under conditions of digitalization

A closer look at the list of factors selected for modelling shows that some of them can already be considered as relative indicators: The share of the average number of full-time employees in the average number of full-time employees in the economy of Ukraine as a whole, %; Share of the number of non-registered employees in the total average number of employees, %; The ratio of the average monthly salary of full-time employees to the average monthly salary in the Ukrainian economy as a whole, %. And the data in Table 2 show that these relative indicators are quite stable over the years within each industry, but vary considerably across industries (indicators values may differ by several times or even by an order of magnitude). Moreover, it can be observed that for these relative indicators in general, there are similarities in their values for industries that are separately classified as high-tech and export-oriented industries, and also high-tech services.

However, when attempting to calculate additional relative indicators, they demonstrate similar behaviour. For example, when dividing Gross profit, mixed income (in consumer prices) by Output (in consumer prices), we get a profitability rate of a few percent for industrial sectors, and close to 30% for high-tech services. A similar situation is observed with other relative indicators calculated in a similar way.

That is, the situation does not fundamentally change compared to the grouping of industries based on absolute values of indicators which these industries characterize in terms of the structure of employed and economic development. Accordingly, it is virtually impossible to study trends of changes in the status of various industries in dynamics under conditions of digitalization on the basis of such indicators.

In order to get around this problem, it is necessary to move from absolute values of indicators for each year to relative annual changes in these indicators. This will allow studying dynamics of changes for each indicator regardless of its level and thus see how each industry has changed annually under conditions of digitalization. Converting the indicators from Table 2 to such relative annual changes will result in one less observation – starting with the ratio of each indicator's value in 2014 to its value in 2013 and so on to the relative change in 2020 to 2019, as can be seen in Table 3.

During clustering of industries on this set of relative values of changes in basic indicators, all observations were evenly distributed across the Kohonen map (whereby virtually every one of these relative indicators was also fairly evenly distributed across the map). Their standardization, which often helps to strengthen differences between groups of homogeneous objects, also proved to be fruitless in this case.

Table 3

DATABASE WITH RELATIVE ANNUAL CHANGES IN INDICATORS OF LABOUR MARKET AND ECONOMIC DEVELOPMENT OF INDUSTRIAL SECTORS AND HIGH-TECH SERVICES

Industry	Year	Average number of full-time employees	The share of the average number of full-time employees in the average number of full-time employees in the economy of Ukraine as a whole	Average number of non-registered employees (attracted on the terms of civil law contracts and external part-time workers)	Share of the number of non-registered employees in the total average number of employees	Output (in consumer prices)	Gross profit, mixed income (in consumer prices)	Average monthly salary of full-time employees (nominal)	The ratio of the average monthly salary of full-time employees to the average monthly salary in the Ukrainian economy as a whole	Average monthly salary of full-time employees (real - adjusted by consumer price index)	Remuneration of salaried employees	Gross value added (in consumer prices)	Gross domestic product (in consumer prices)
1	2	3	4	5	6	7	8	9	10	11	12	13	14
Pharmacy	2014/2013	1,048	1,087	1,000	1,000	1,208	1,947	1,147	1,077	1,020	1,445	1,602	1,331
Pharmacy	2015/2014	0,955	1,040	0,833	0,882	1,293	1,647	1,327	1,101	1,001	1,160	1,356	1,440
Pharmacy	2016/2015	1,048	1,077	1,000	0,957	1,379	1,566	1,336	1,081	1,744	1,079	1,299	1,259
Pharmacy	2017/2016	1,045	1,071	0,867	0,886	1,087	1,073	1,256	0,916	1,250	1,292	1,169	1,224
Pharmacy	2018/2017	1,043	1,033	1,000	0,910	1,153	0,982	1,210	0,970	1,261	1,439	1,189	1,222
Pharmacy	2019/2018	1,000	1,032	0,923	0,926	1,234	1,064	1,165	0,984	1,228	1,175	1,125	1,080
Pharmacy	2020/2019	1,042	1,063	1,333	1,345	1,093	1,023	1,083	0,981	1,074	1,084	1,057	1,090
Computers	2014/2013	0,733	0,804	0,909	1,225	1,157	1,299	1,041	0,982	0,925	1,042	1,081	1,085
Computers	2015/2014	0,909	1,000	0,800	0,886	1,169	0,718	1,438	1,193	1,084	1,105	1,025	1,310
Computers	2016/2015	1,033	1,054	1,125	1,085	1,498	2,792	1,469	1,189	1,919	1,446	1,613	1,270
Computers	2017/2016	0,871	0,897	0,778	0,945	1,232	0,378	1,326	0,968	1,320	1,338	1,111	1,623
Computers	2018/2017	1,037	1,057	1,143	1,040	1,116	2,539	1,182	0,947	1,232	1,149	1,258	1,023
Computers	2019/2018	0,929	0,946	0,875	0,946	1,073	1,027	1,176	0,993	1,240	1,124	1,109	1,062
Computers	2020/2019	0,923	0,943	0,857	1,053	0,972	0,260	1,061	0,961	1,052	0,766	0,691	0,918
Electrics	2014/2013	1,000	1,133	1,048	0,997	1,087	1,103	1,044	0,985	0,929	1,077	1,074	1,101
Electrics	2015/2014	0,869	0,971	0,955	1,095	1,086	1,990	1,225	1,017	0,924	0,794	1,062	1,174
Electrics	2016/2015	0,925	0,939	1,095	1,176	1,176	1,377	1,241	1,004	1,620	1,026	1,161	1,134
Electrics	2017/2016	1,020	1,048	0,826	0,848	1,300	1,130	1,424	1,039	1,418	1,354	1,242	1,558
Electrics	2018/2017	1,000	1,000	0,947	0,916	1,239	1,206	1,276	1,023	1,330	1,400	1,312	1,184
Electrics	2019/2018	0,900	0,938	0,889	0,986	1,020	0,952	1,163	0,982	1,226	0,972	0,964	0,971
Electrics	2020/2019	0,933	0,934	0,938	1,041	0,956	0,559	1,037	0,940	1,028	1,017	0,830	0,913

1	2	3	4	5	6	7	8	9	10	11	12	13	14
Food	2014/2013	0,926	1,006	0,959	1,034	1,094	1,465	1,071	1,010	0,862	1,082	1,237	1,210
Food	2015/2014	0,898	0,997	1,092	1,204	1,246	1,502	1,254	1,040	1,093	1,138	1,303	1,374
Food	2016/2015	0,972	0,994	0,904	0,934	1,212	1,447	1,239	1,002	1,579	1,004	1,224	1,312
Food	2017/2016	0,993	1,020	0,807	0,822	1,202	1,032	1,304	0,951	1,289	1,385	1,159	1,274
Food	2018/2017	0,982	0,984	0,808	0,829	1,110	0,948	1,234	0,989	1,278	1,214	1,050	1,105
Food	2019/2018	1,065	1,097	0,886	0,837	1,071	1,009	1,198	1,011	1,263	1,149	1,078	1,048
Food	2020/2019	0,976	0,987	0,882	0,906	1,136	1,276	1,078	0,976	1,068	1,122	1,199	1,227
Metallurgy	2014/2013	0,877	0,953	0,800	0,915	1,182	5,940	1,128	1,064	0,908	1,203	1,724	1,680
Metallurgy	2015/2014	0,897	0,997	0,917	1,019	1,264	1,244	1,206	1,000	1,051	1,078	1,139	1,188
Metallurgy	2016/2015	0,893	0,914	1,109	1,236	1,203	1,551	1,190	0,963	1,517	1,012	1,222	1,223
Metallurgy	2017/2016	0,950	0,975	0,885	0,934	1,287	1,238	1,254	0,915	1,240	1,340	1,281	1,248
Metallurgy	2018/2017	0,918	0,919	0,944	1,028	1,181	1,198	1,309	1,049	1,355	1,196	1,195	1,197
Metallurgy	2019/2018	1,016	1,044	0,784	0,778	0,929	0,806	1,220	1,031	1,287	1,024	0,910	0,920
Metallurgy	2020/2019	0,959	0,973	0,925	0,966	0,901	0,824	1,035	0,938	1,026	0,972	0,902	0,901
Chemicals	2014/2013	0,949	1,038	1,000	1,051	1,018	0,260	1,091	1,029	0,878	0,906	1,030	1,045
Chemicals	2015/2014	0,838	0,928	0,880	1,049	1,405	-4,31	1,256	1,042	1,095	1,139	1,409	1,769
Chemicals	2016/2015	0,968	0,987	1,045	1,076	1,038	1,192	1,189	0,963	1,516	0,930	0,942	0,953
Chemicals	2017/2016	0,933	0,961	1,130	1,203	1,124	0,428	1,273	0,929	1,258	1,275	1,109	1,218
Chemicals	2018/2017	1,000	1,000	0,615	0,626	1,163	2,990	1,165	0,933	1,206	1,046	1,187	1,137
Chemicals	2019/2018	0,964	1,000	0,875	0,910	1,028	0,352	1,289	1,089	1,360	1,105	0,967	1,022
Chemicals	2020/2019	1,037	1,041	1,000	0,964	0,934	0,846	1,090	0,987	1,081	1,015	1,001	0,984
Telecom	2014/2013	0,853	0,967	0,890	1,040	1,078	1,141	1,125	1,055	1,001	1,006	1,090	1,063
Telecom	2015/2014	0,854	0,949	0,863	1,009	1,420	1,519	1,374	1,140	1,036	1,091	1,377	1,366
Telecom	2016/2015	0,910	0,934	1,206	1,290	1,283	1,364	1,340	1,085	1,750	1,128	1,230	1,229
Telecom	2017/2016	0,975	1,000	0,770	0,887	1,231	1,211	1,261	0,920	1,256	1,252	1,236	1,231
Telecom	2018/2017	0,992	0,994	1,120	0,910	1,271	1,246	1,188	0,952	1,238	1,282	1,259	1,258
Telecom	2019/2018	0,949	0,981	1,099	1,273	1,283	1,300	1,229	1,038	1,296	1,350	1,316	1,292
Telecom	2020/2019	0,946	0,954	0,604	0,721	1,076	1,257	1,134	1,027	0,952	1,076	1,146	1,135
R&D	2014/2013	0,904	1,027	0,835	0,930	1,048	1,267	1,061	0,995	1,071	1,013	1,097	…
R&D	2015/2014	0,933	1,034	1,094	1,156	1,239	1,317	1,165	0,967	0,943	0,913	1,069	…
R&D	2016/2015	0,938	0,967	0,914	0,976	0,959	0,937	1,231	0,997	0,878	1,008	0,975	0,955
R&D	2017/2016	0,956	0,974	0,813	0,940	1,130	0,976	1,342	0,979	1,606	1,506	1,258	1,266
R&D	2018/2017	1,069	1,071	1,115	0,953	1,347	1,378	1,249	1,001	1,739	1,345	1,352	1,388
R&D	2019/2018	0,849	0,876	0,954	1,112	1,093	0,728	1,135	0,959	1,198	0,903	0,836	0,842
R&D	2020/2019	0,987	1,000	0,916	1,024	1,033	1,328	1,106	1,001	1,096	1,027	1,045	1,033

Therefore, a series of experiments on selecting factors from the full set presented in Table 3 for clustering had to be conducted. First of all, 3 relative indicators re calculated on the basis of already relative coefficients were discarded – The share of the average number of full-time employees in the average number of full-time employees in the economy of Ukraine as a whole, Share of the number of non-registered employees in the total average number of employees, The ratio of the average monthly salary of full-time employees to the average monthly salary in the Ukrainian economy as a whole. This was done, among other things, because there are other indicators in the set of factors that are substitutes for these ones, but calculated on absolute values. The experimental research gave grounds to exclude the relative change indicator calculated on the basis of Gross profit, mixed income (in consumer prices), as it also has duplicate indicators: Gross value added (in consumer prices) and Gross domestic product (in consumer prices).

The result of clustering high-tech and export-oriented industries and high-tech services based on the compiled list of 8 coefficients of annual changes in labour market and economic development indicators is shown in Fig. 7.

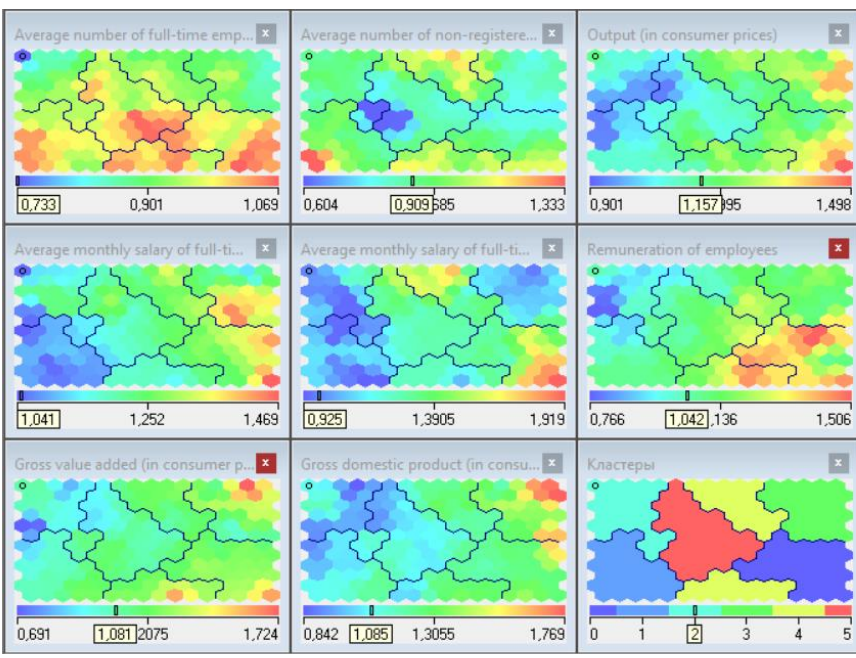

Fig. 7. Distribution of values of indicators' relative changes on the Kohonen map

The heat maps in Fig. 7 clearly show changes in the levels of indicators for different clusters, which indicates the identification of patterns in the set of studied objects (industries) and their distribution into homogeneous groups. Table 4 shows results of industries distribution by cluster over the years.

Table 4

RESULT OF INDUSTRIAL AND HIGH-TECH SERVICES SECTORS CLUSTERING BASED ON ANNUAL CHANGES IN CHARACTERISTIC INDICATORS

Cluster	Year	Industry
0	2016/2015	Pharmacy, Computers
	2017/2016	Electrics, Food, Metallurgy, Telecom, R&D
	2018/2017	Pharmacy, Electrics, R&D
1	2014/2013	Electrics, Food, Chemicals
	2020/2019	Pharmacy, Electrics, Food, Metallurgy, Chemicals, R&D
2	2014/2013	Computers, Telecom
	2015/2014	Electrics
	2016/2015	R&D
	2019/2018	Electrics, R&D
	2020/2019	Computers, Telecom
3	2014/2013	Metallurgy
	2015/2014	Pharmacy, Computers, Food, Metallurgy, Chemicals, Telecom
	2017/2016	Computers
4	2014/2013	Pharmacy
	2016/2015	Electrics, Food, Metallurgy, Telecom
	2017/2016	Chemicals
	2018/2017	Computers, Metallurgy, Telecom
	2019/2018	Telecom
5	2016/2015	Chemicals
	2017/2016	Pharmacy
	2018/2017	Food, Chemicals
	2019/2018	Pharmacy, Computers, Food, Metallurgy, Chemicals

As can be seen from Table 4, cluster 1 (located in the lower left corner of the Kohonen map, which is evident from the markings of the last map in Fig. 7) contains observations for most industries only for 2 periods – 2014 to 2013, and 2020 to 2019. That is, during the most difficult years in the entire period of observation in this study – beginning of Russian aggression against Ukraine in 2014 and the first year of COVID-19 pandemic, when the economy and social sphere experienced significant challenges. For two more industries, Computers and Telecom, observations for these two periods fell into cluster 2, which is adjacent to the first one (moreover, to neurons that are close to the first cluster). According to the selected indicators, Pharmacy industry was placed in the lower left part of the fourth cluster. That is, in terms of the dynamics of changes of labour market and economic development, all industries in 2014 and 2020 were grouped in the lower left part of the Kohonen map.

According to Table 3, these periods are characterized by lower growth in Output (in consumer prices) and Average monthly salary of full-time employees (nominal) compared to other years, even though these indicators are measured in UAH and it was in 2014 and 2020 that the UAH exchange rate depreciated the most (i.e., in comparable prices, there would have been a significant decline in these indicators in general).

However, for other indicators, differences in indicators by industries are observed both for these and other periods. For example, employment indicators (Average number of full-time employees and Average number of non-registered employees (attracted on the terms of civil law contracts and external part-time workers)) for high-tech industries and high-tech services sectors (especially for Manufacture of computers, electronic and optical products and Information and telecommunications) experienced the largest declines in 2014 and 2020 compared to other industries. Meanwhile, in other years, the trend was reversed – these industries demonstrated the largest increase in the number of full-time and non-registered employees.

Essentially, this can be explained by the fact that industries with large production facilities have historically been much more inertial in recruiting and dismissing personnel. In this sense, high-tech services sector is much more mobile, and in the event of economic turmoil, it is much easier to lay off employees as well as to recruit specialists when economic conditions improve.

It is also worth noting that in 2020, due to the spread of the COVID-19 pandemic, there was a significant decline in business activity around the world and a decrease in personal contacts between people. And while in industrial sectors manufacturing facilities cannot operate without direct involvement of human resources, and therefore there was almost no layoffs, high-tech industries (primarily in high-tech services) have experienced a real boom in transition to an online work format.

Approximately a similar situation, albeit on a somewhat smaller scale, occurred in Ukraine in 2014, when, in the context of Russian aggression, a significant number of specialists were forced to relocate and, among other things, switch to online format at those enterprises where it was possible (with the exception of industrial enterprises, obviously).

In summary, despite very serious economic challenges and real problems in most industries, 2014 and 2020 can be considered years of rapid development of digital technologies in high-tech industries (which fall into clusters 1 and 2 on the Kohonen map – see Table 4). As can be seen from the values of these industries' indicators in Table 3, such transformations were accompanied by a reduction in the number of employees and a decrease in salaries (although this was not a direct consequence of the use of digital technologies – rather, technologies were introduced as a result of problems in the respective industries).

And while the lower left corner of the Kohonen map is occupied by industries that have undergone the greatest transformation towards the digital economy, then according to the principles of cluster analysis, the opposite right side of the map corresponds to industries with the least digital transformation. These are mainly industrial sectors by the years of Ukraine's economic recovery from 2015 to 2018.

Research on the impact of employment indicators in the field of high-tech activities on indicators of macroeconomic dynamics

In order to find new opportunities for macroeconomic growth, the authors of the article, using the data of the State Statistics Service of Ukraine [48], predicted both the Gross domestic product (GDP) (see

Fig. 8) and Gross value added (GVA) (see Fig. 9) in the economy of Ukraine by determining a linear trend (as the most appropriate one for the existing dynamics) with the allocation of upper and lower confidence limits in the trend, which characterize optimistic, realistic and pessimistic scenarios for the abovementioned indicators' development.

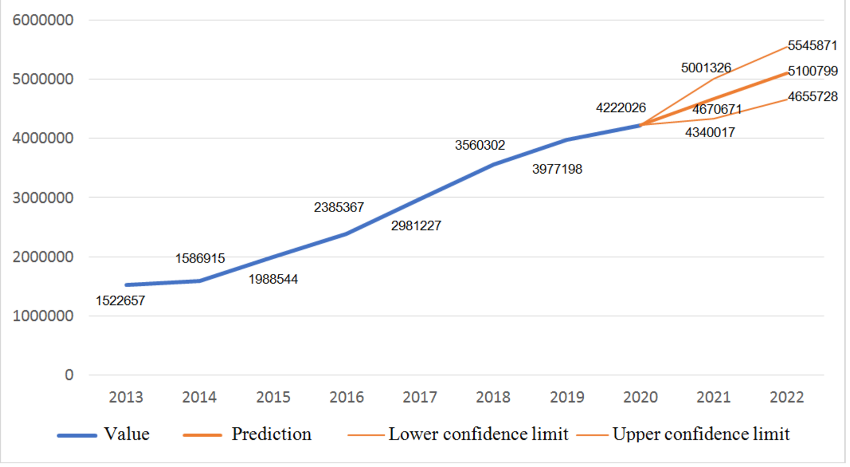

Fig. 8. Dynamics of gross domestic product in the economy of Ukraine (in actual prices, UAH million)

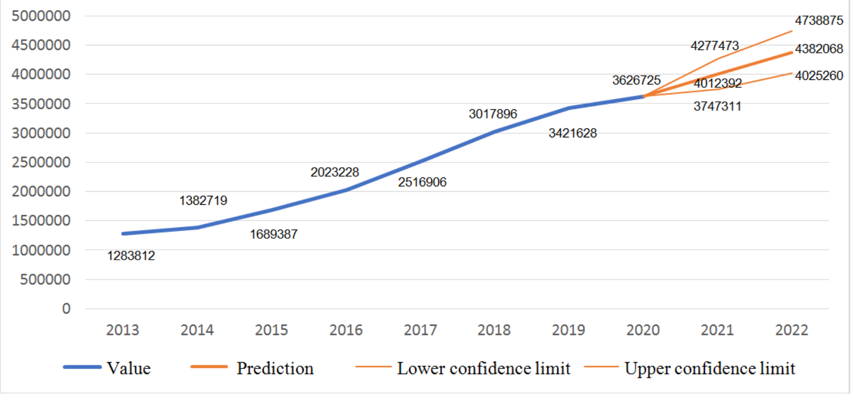

Fig. 9. Dynamics of gross value added in the economy of Ukraine (in basic prices, UAH million)

A hypothesis is put forward that the probability of implementing the optimistic scenario of GDP and GVA dynamics under conditions of digitalization can be increased by optimizing the number and structure of those employed in the high-tech segment.

In order to identify the dependence of Gross domestic product and Gross value added in the high-tech segment on the number and structure of employed, economic and mathematical models for forecasting these indicators were built on the basis of multifactor regression using such exogenous variables as Average number of full-time employees, '000 people (X_1); The share of the average number of full-time employees in the average number of full-time employees in the economy of Ukraine as a whole, % (X_2); Average number of non-registered employees (attracted on the terms of civil law contracts and external part-time workers), '000 people (X_3); Share of the number of non-registered employees in the total average number of employees, % (X_4); Average monthly salary of full-time employees (nominal), UAH (X_5).

Results of forecasting the gross domestic product and gross value added in certain export-oriented sectors of the economy of Ukraine are presented for comparison to argue for the effect of employment in the high-tech segment of the economy (see Table 5). Among the selected exogenous factors, the first four reflect absolute (number) and relative (share) employment indicators, and the fifth factor allows to assess in a generalized way the impact of employee qualifications and labour productivity, since the amount of nominal salary in part of the basic salary depends on employee qualifications, and in part of the additional salary – on both employee qualifications and labour productivity.

Sensitivity analysis of each multifactor regression, based on the elasticity coefficient $E(Y/X_i)$, revealed the degree of influence of each exogenous factor on GDP and GVA by areas of economic activity and industries. The elasticity coefficient $E(Y/X_i)$ shows by how many percent the resulting indicator will change (increase/decrease) if the corresponding exogenous variable increases by 1%. Table 6 shows the main characteristics of employment indicators impact in high-tech segment and certain export-oriented industries on macroeconomic indicators, which suggest that one of the prerequisites for ensuring an optimistic scenario of positive macroeconomic dynamics is to improve the employment structure.

Table 5

A FORMALIZED VIEW OF MACROECONOMIC INDICATORS' DEPENDENCE ON SELECTED EXOGENOUS FACTORS

Macroeconomic indicator / **Scope of activities**	**Gross Domestic Product**	**Gross Value Added**
High-tech manufacturing		
Manufacture of basic pharmaceutical products and pharmaceuticals	$Y_1 = –3877{,}44 – 1398{,}50 \cdot X_1 + 192838{,}29 \cdot X_2 + 14132{,}97 \cdot X_3 – 4151{,}97 \cdot X_4 + 0{,}5957 \cdot X_5$	$Y_2 = –791{,}11 – 1087{,}40 \cdot X_1 + 130951{,}98 \cdot X_2 + 111150{,}47 \cdot X_3 – 3073{,}24 \cdot X_4 + 0{,}0160 \cdot X_5$
Manufacture of computers, electronic and optical products	$Y_1 = 31351{,}30 – 621{,}57 \cdot X_1 + 3989{,}47 \cdot X_2 + 8695{,}44 \cdot X_3 – 4781{,}21 \cdot X_4 + 1{,}16 \cdot X_5$	$Y_2 = 14791{,}86 – 533{,}95 \cdot X_1 + 7232{,}95 \cdot X_2 + 10261{,}28 \cdot X_3 – 3411{,}31 \cdot X_4 + 0{,}47 \cdot X_5$
Manufacture of electrical equipment	$Y_1 = –129458 + 1221{,}58 \cdot X_1 + 68276{,}22 \cdot X_2 – 23072{,}30 \cdot X_3 + 17436{,}99 \cdot X_4 + 3{,}34 \cdot X_5$	$Y_2 = –40355{,}70 + 260{,}04 \cdot X_1 + 17120{,}82 \cdot X_2 + 5041{,}82 \cdot X_3 + 1082{,}52 \cdot X_4 + 1{,}93 \cdot X_5$
Certain export-oriented industries		
Manufacture of food, beverages and tobacco products	$Y_1 = 581406{,}90 – 1116{,}25\ X_1 – 56390{,}20\ X_2 + 7357{,}77\ X_3 – 25099{,}70\ X_4 + 31{,}63\ X_5$	$Y_2 = 198113{,}20 – 714{,}67\ X_1 + 10444{,}94\ X_2 + 8094{,}28\ X_3 – 23075\ X_4 + 9{,}22\ X_5$
Metallurgical production, manufacture of fabricated metal products (except machinery and equipment)	$Y_1 = –905089 + 2630{,}42\ X_1 + 82854{,}86\ X_2 – 125963{,}00\ X_3 + 321540{,}30\ X_4 + 8{,}82\ X_5$	$Y_2 = –840689{,}00 + 2592{,}35\ X_1 + 67437{,}52\ X_2 – 121619{,}00\ X_3 + 306940{,}50\ X_4 + 7{,}93\ X_5$
Manufacture of chemicals and chemical products)	$Y_1 = –130691 + 2538{,}28\ X_1 + 18764{,}83\ X_2 – 103047\ X_3 + 60003{,}19\ X_4 – 0{,}07\ X_5$	$Y_2 = –56218{,}50 + 1045{,}09\ X_1 + 12591{,}02\ X_2 – 40984{,}10\ X_3 + 23627{,}42\ X_4 – 0{,}17\ X_5$
High-tech services		
Information and telecommunications	$Y_1 = 164364{,}85 – 65{,}67 \cdot X_1 + 97287{,}61 \cdot X_2 – 0{,}03 \cdot X_3 + 3{,}16 \cdot X_4 + 2{,}21 \cdot X_5$	$Y_2 = –172907{,}68 – 20{,}96 \cdot X_1 + 98342{,}43 \cdot X_2 – 569{,}96 \cdot X_3 + 126{,}57 \cdot X_4 + 12{,}21 \cdot X_5$
Research and development	$Y_1 = –24799{,}10 – 9{,}03 \cdot X_1 + 33507{,}85 \cdot X_2 + 532{,}80 \cdot X_3 – 1504{,}18 \cdot X_4 + 1{,}69 \cdot X_5$	$Y_2 = –20870{,}60 + 35{,}58 \cdot X_1 + 28279{,}38 \cdot X_2 + 168{,}20 \cdot X_3 – 1277{,}92 \cdot X_4 + 1{,}48 \cdot X_5$

Table 6

DEGREE OF EXOGENOUS FACTORS' IMPACT ON MACROECONOMIC INDICATORS BY SCOPES OF ACTIVITIES

Macroeconomic indicator	**Gross domestic product**					**Gross value added**				
Elasticity	$E(Y_1/X_1)$	$E(Y_1/X_2)$	$E(Y_1/X_3)$	$E(Y_1/X_4)$	$E(Y_1/X_5)$	$E(Y_2/X_1)$	$E(Y_2/X_2)$	$E(Y_2/X_3)$	$E(Y_2/X_4)$	$E(Y_2/X_5)$
Scope of activity	*High-tech manufacturing*									
Manufacture of basic pharmaceutical products and pharmaceuticals	-1,43	2,48	0,95	-1,17	0,34	-2,57	3,89	1,74	2,00	0,02
Manufacture of computers, electronic and optical products	-1,54	0,12	1,17	-2,04	0,75	-4,15	0,69	4,32	-4,57	0,94
Manufacture of electrical equipment	3,62	2,48	-2,58	3,71	1,23	1,35	1,09	0,99	0,40	1,25
Certain export-oriented industries										
Manufacture of food, beverages and tobacco products	-1,40	-0,88	0,42	-0,46	0,86	-2,28	0,41	1,17	-1,07	0,64
Metallurgical production, manufacture of fabricated metal products (except machinery and equipment)	9,32	3,60	-10,62	11,63	1,17	10,00	3,19	-11,17	12,09	1,14
Manufacture of chemicals and chemical products)	7,62	0,69	-10,29	9,33	-0,02	7,84	1,16	-10,23	9,19	-0,15
High-tech services										
Information and telecommunications	-0,07	1,27	0,01	-0,05	1,17	-0,02	1,39	-0,07	0,01	1,22
Research and development	-0,05	2,27	0,29	-0,83	0,79	0,21	2,01	0,10	-0,74	0,72

In particular, in the models of Gross domestic product and Gross value added dependence on exogenous factors, the share of the average number of full-time employees in high-tech industrial sector “Manufacture of basic pharmaceutical products and pharmaceuticals”, export-oriented industrial sector “Metallurgical production, manufacture of fabricated metal products (except machinery and equipment)” and high-tech services sectors (“Information and telecommunications”, “Research and development”) in the average number of full-time employees in the economy as a whole has the largest positive impact on their change. On the other hand, for the high-tech industry “Manufacture of computers, electronic and optical products” and the export-oriented industry “Manufacture of chemicals and chemical products”, the share of the number of non-registered employees in the total average number of employees has the strongest impact on macroeconomic dynamics. Herewith, the elasticity coefficient is negative in the first of these industries, and positive in the second, which means that it would be advisable to reduce the scale of employment of workers on the terms of civil law contracts and external part-time workers in the high-tech industry “Manufacture of computers, electronic and optical products” and, accordingly, to increase the share of this category of employees in the export-oriented industry “Manufacture of chemicals and chemical products”.

The values of elasticity coefficients we obtained indicated that the average monthly salary of full-time employees in the studied industries, which, according to our assumption, indirectly reflects the qualification component of the employed, is not the dominant exogenous factor influencing changes in Gross domestic product and Gross value added.

Conclusions

Critical synthesis of available scientific findings, carried out with the aim of developing the theoretical construct of the employment-XXI model, demonstrates the dynamic scaling of digital economy in global economic space, which causes profound multi-vector shifts in employment sphere on the level of national economies and their spheres, industries, and segments. Development of digital technologies, which produce new employment mechanisms, influences job system reformatting with the elimination of a significant share of traditional jobs and, in parallel, with an increase in the scale of employment based on the potential of breakthrough technologies of digital age.

One of the vectors of economic digitalization in social and labour space is the formation of digital employment, the subject of which is a "digital employee" – an economically active person with digital competencies who provides digital services (basic smart-employment) and creates new digital products or improves existing ones (digital smart-employment).

The authors' hypothesis, which was substantiated in this article, is the assumption that the scale and structure of employment under the influence of digitalization will change intensively in at least two dimensions – constructive and destructive. Constructivism of such changes will be manifested in scaling up employment of representatives of professions that are in demand in digitalization era (the "rising stars" group) and will have a constructive, generative character of changes, while the destructiveness, respectively, will be manifested in a significant reduction in employment of representatives of professions whose functions during digitalization era are taken over (the "dying professions" group) and will have a predominantly destructive, "emasculating" character of changes.

The authors make a reasonable assumption that professions in demand in the digital era are mostly concentrated in the high-tech segment, where both the creation of digital products and their general usage take place.

An analysis of trends based on statistical data from the International Labour Organization suggests that employment rates globally, in Europe as a whole, and in Ukraine will not show a downward trend in the near future, and unemployment will be declining in the short term, delaying predicted "unemployed future" in time.

There is every reason to conclude that one of the defining trends in the rise of digital economy is the growth of high-tech sector, where employment optimization, in our opinion, will contribute to improvement of macroeconomic situation both globally and nationally.

The impact of employment in a number of high-tech industries and high-tech services sectors on dynamics of such macroeconomic indicators as gross domestic product and gross value added was studied in order to verify reliability and substantiation of our hypothesis that constructive and destructive effects of digitalization can be enhanced, reduced or completely eliminated depending on the action of a number of factors that determine the sectoral structure of employment. For this purpose, the authors of the article have formed a set of characteristic socio-labour and socio-economic indicators using the cluster analysis methodology and Kohonen self-organizing maps toolset, which allowed, based on the data of the State Statistics Service of Ukraine for the period from 2013 to 2020, to analyze the state of development of each industry by the structure of employed and economic development among other sectors of economy, as well as to study trends in changes in industry state in dynamics under conditions of digitalization.

As a result of using Deductor Studio Academic software package for building self-organizing maps, an uninformative clustering result was obtained, which confirmed the separate distribution of industries into seven clusters, since the industries are too different from each other primarily in terms of economic development and to a lesser extent, although still significantly, in terms of the number and structure of employed.

According to constructed Kohonen self-organizing map, in terms of profitability and salary (nominal and real), high-tech service organizations (R&D and especially Information and Telecommunications) significantly prevail over certain high-tech and export-oriented industries (Manufacture of computers, electronic and optical products, Manufacture of electrical equipment, and Manufacture of chemicals and chemical products).

Since the differences between the values of indicators in different industries vary greatly, it is not advisable to standardize or normalize them in order to reduce the excessive influence of individual indicators. Therefore, a set of relative predictors was formed in order to study dynamics of industries' development in comparative dimensions. As a result of industries' clustering based on a set of relative values of changes in basic indicators, all observations were evenly distributed across the Kohonen map, and their standardization, which often helps to strengthen differences between groups of homogeneous objects, also turned out to be ineffective. A series of experiments on selecting factors for further clustering allowed identifying changes in the levels of indicators for different clusters, which confirmed the regularities in the set of studied objects (industries) and their distribution into homogeneous groups, taking into account the time factor – 2014 to 2013, and 2020 to 2019, i.e., at the beginning of Russian aggression against Ukraine in 2014 and in the first year of COVID-19 pandemic, when economy and social sphere experienced significant challenges.

At the same time, employment indicators (Average number of full-time employees and Average number of non-registered employees (attracted on the terms of civil law contracts and external part-time workers)) for high-tech industries and high-tech services sectors (especially for Manufacture of computers, electronic and optical products and Information and telecommunications) in 2014 and 2020 showed the largest decrease compared to other industries. In contrast, in other years the opposite trend was observed – the growth in the number of full-time employees and non-registered personnel in these industries was the largest. The argument for the identified trends can be, firstly, historically formed much greater inertia in recruiting and dismissing personnel in industries with large production enterprises and significant mobility of personnel processes in the field of high-tech services, which has been confirmed by the need to maintain standard employment in industrial sector of Ukraine's economy and to scale up online format of labour activity and relocation of employees in the field of high-tech services during COVID-19 pandemic and at the beginning of Russian military aggression. Thus, according to the results of clustering, 2014 and 2020 can be considered the years of rapid development of digital technologies in high-tech industries that fell into clusters 1 and 2 on the Kohonen map we have built.

Our forecasts of gross domestic product and gross value added in Ukraine's economy, with identification of upper and lower confidence limits in the trend, allowed us to model optimistic, realistic and pessimistic scenarios for these macroeconomic indicators. At the same time, a hypothesis has been put forward and proven that probability of realization of optimistic scenario for dynamics of gross domestic product and gross value added under conditions of digitalization can be increased by optimizing the number and structure of employees in high-tech segment. This is substantiated by the multi-factor regression equations and elasticity coefficients' values, which characterize the degree of influence of each exogenous factor on resulting indicators by spheres of economic activity and industries. Thus, according to the modeling results, the largest positive impact of such an exogenous variable as the share of the average number of full-time employees in the high-tech industrial sector "Manufacture of basic pharmaceutical products and pharmaceuticals" and high-tech services sectors ("Information and telecommunications", "Research and development") in the average number of full-time employees in the economy of Ukraine as a whole on dynamics of gross domestic product and gross value added was revealed. In contrast, advisability of reducing the scale of attracting employees under civil law contracts and external part-time workers in the high-tech industry "Manufacture of computers, electronic and optical products" and increasing the share of such category of employees in export-oriented industry "Manufacture of chemicals and chemical products" has been foreseen. The average monthly salary of full-time employees in studied industries, which, as an exogenous factor, indirectly reflects qualification component of employed, is not the dominant factor influencing changes in gross domestic product and gross value added.

As the study results demonstrate, modeling dependencies of macroeconomic indicators on metrics that directly or indirectly characterize quantitative and qualitative determinants of employment in digital economy on the basis of industry, allows developing a scientific and applied construct of the employment-XXI model and identifying vectors for improving employment policies, mechanisms and toolset in national economies for sustainable socio-economic development.

We urge everyone who studies employment issues to jointly expand the horizons of scientific research, go beyond the essence of certain mono-phenomena and processes, and not play terminological jousting by considering secondary phenomena and processes that do not contribute to the growth of knowledge. In the greater scheme of things, the point is not so much in new terms, statement of obvious facts, demonstration of disordered statistical data that have flooded economic, social and labour literature, but in a fundamental understanding and applied research (using economic and mathematical modeling tools) of the nature of phenomena and processes of standard/non-standard typical/atypical, traditional/remote employment that unfold in the "field" of social and labour development of the digital age, their obvious and latent essential characteristics that lay foundation for a new reality in the world of labour and employment.

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References

1. Jia, Z., & Vattø, T. E. (2021). Predicting the path of labor supply responses when state dependence matters. *Labour Economics, 71*(C), Article 102004. https://doi.org/10.1016/j.labeco.2021.102004

2. Van der Zwan, P., Hessels, J., & Rietveld, C.A. (2018). Self-employment and satisfaction with life, work, and leisure. *Journal of Economic Psychology*, *64*, 73-88. https://doi.org/10.1016/j.joep.2017.12.001

3. Cowling, M., Millán, J. M., & Yue, W. (2019). Two decades of European self-employment: Is the answer to who becomes self-employed different over time and countries? *Journal of Business Venturing Insights, 12*(C), Article e00138. https://doi.org/10.1016/j.jbvi.2019.e00138

4. Nolan, A., & Barrett, A. (2019). The role of self-employment in Ireland's older workforce. *The Journal of the Economics of Ageing, 14*(C), Article 100201. https://doi.org/10.1016/j.jeoa.2019.100201

5. Patel, Pankaj C. & Wolfe, Marcus T. (2019). Money might not make you happy, but can happiness make you money? The value of leveraging subjective well-being to enhance financial well-being in self-employment. *Journal of Business Venturing Insights*, *12*(C), Article e00134. https://doi.org/10.1016/j.jbvi.2019.e00134

6. Stenard, B. S. (2019). Are transitions to self-employment beneficial? *Journal of Business Venturing Insights, 12*(C), Article e00131. https://doi.org/10.1016/j.jbvi.2019.e00131

7. Lee, N., & Clarke, S. (2019). Do low-skilled workers gain from high-tech employment growth? High-technology multipliers, employment and wages in Britain. *Research Policy*, *48*(9), Article 103803. https://doi.org/10.1016/j.respol.2019.05.012

8. Sheehan, P., & Shi, H. (2019). Employment and Productivity Benefits of Enhanced Educational Outcomes: A Preliminary Modelling Approach. *Journal of Adolescent Health*, *65*(1), 44-51. https://doi.org/10.1016/j.jadohealth.2019.03.025

9. He, Y., Peng, X., & Xu, H. (2020). Overeducation, market recognition, and effective labour supply. *China Economic Review*, *59*(C), Article 101384. https://doi.org/10.1016/j.chieco.2019.101384

10. Kergroach, S. (2017). Industry 4.0: New Challenges and Opportunities for the Labour Market. *Foresight and STI Governance, 11*(4), 6–8. https://doi.org/10.17323/2500-2597.2017.4.6.8

11. Wadley, D. (2021). Technology, Capital Substitution and Labor Dynamics: Global Workforce Disruption in the 21st Century? *Futures*, *132*, Article 102802. https://doi.org/10.1016/j.futures.2021.102802

12. Zhang, F., Meng, L., Sun, W., & Si, Y. (2021). Information technology and the labor market in China. *Economic Analysis and Policy, 72*(C), 156-168. https://doi.org/10.1016/j.eap.2021.06.015

13. Giddens, A. (2002). *Runaway World: How Globalization is Reshaping Our Lives*. Profile Books.

14. Rifkin, J. (1995). *The end of work: The decline of the global labor force and the dawn of the post-market era*. G. P. Putnam's Son. http://pinguet.free.fr/rifkin1995.pdf

15. Hines, A. (2019). Getting Ready for a Post-Work Future. *Foresight and STI Governance*, *13*(1), 19–30. https://doi.org/10.17323/2500-2597.2019.1.19.30

16. Kolot, A., & Herasymenko, O. (2017). Market, state and business in coordinates of the new economy. *Problems and Perspectives in Management*, *15*(3), 76-97. http://dx.doi.org/10.21511/ppm.15(3).2017.07

17. Kolot, A., Kozmenko, S., Herasymenko, O., & Štreimikienė, D. (2020). Development of a Decent Work Institute as a Social Quality Imperative: Lessons for Ukraine. *Economics and Sociology*, *13*(2), 70-85. https://doi.org/10.14254/2071-789X.2020/13-2/5

18. Kolot, A., Herasymenko, O., & Yarmolyuk-Kröck, K. (2020). *Impact of COVID-19 pandemic on economic development and labor in*

Ukraine. Friedrich Ebert Stiftung. http://library.fes.de/pdf-files/bueros/kiew/17372.pdf

19. Poruchnyk, A., Kolot, A., Mielcarek, P., Stoliarchuk, Y., & Ilnytskyy, D. (2021). Global economic crisis of 2020 and a new paradigm of countercyclical management. *Problems and Perspectives in Management*, *19*(1), 397–415. https://doi.org/10.21511/ppm.19(1).2021.34

20. OECD. (2015). *Data-Driven Innovation: Big Data for Growth and Well-Being*. OECD Publishing. http://dx.doi.org/10.1787/9789264229358-en

21. Kenney, M., & Zysman, J. (2016). The Rise of the Platform Economy. *Issues in Science and Technology*, *32*(3), 61-69. https://issues.org/rise-platform-economy-big-data-work/

22. Fernández-Macías, E., Hurley, J., & Bisello, M. (2016). *What do Europeans do at work? A task-based analysis: European Jobs Monitor*. European Foundation for the Improvement of Living and Working Conditions. https://www.eurofound.europa.eu/publications/report/2016/what-do-europeans-do-at-work-a-task-based-analysis-european-jobs-monitor-2016

23. Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, *114*, 254–280. https://doi.org/10.1016/j.techfore.2016.08.019

24. Huateng, M., Zhaoli, M., Deli, Y., & Hualei, W. (2021). *The Chinese Digital Economy* (G. Kaitian, & S. Xiao, Eds.). Palgrave Macmillan. https://doi.org/10.1007/978-981-33-6005-1

25. Sorgner, A. (2017). The Automation of Jobs: A Threat for Employment or a Source of New Entrepreneurial Opportunities? *Foresight and STI Governance*, *11*(3), 37–48. https://doi.org/10.17323/2500-2597.2017.3.37.48

26. Seidl da Fonseca, R. (2017). The Future of Employment: Evaluating the Impact of STI Foresight Exercises. *Foresight and STI Governance*, *11*(4), 9–22. https://doi.org/10.17323/1995-459X.2016.4.9.22

27. Manyika, J., Chui, M, Miremadi, M., Bughin, J., George, K., Willmott, P., & Dewhurst, M. (2017, January 12). *Harnessing automation for a future that works*. McKinsey Global Institute. https://www.mckinsey.com/featured-insights/digital-disruption/harnessing-automation-for-a-future-that-works

28. Fossen, F., & Sorgner, A. (2019). Mapping the Future of Occupations: Transformative and Destructive Effects of New Digital Technologies on Jobs. *Foresight and STI Governance*, *13*(2), 10–18. https://doi.org/10.17323/2500-2597.2019.2.10.18

29. Chang, J.-H., Rynhart, G., & Huynh, P. (2016). *ASEAN in Transformation: The Future of Jobs at Risk of Automation. Bureau for*

Employers' Activities. International Labour Organization. https://www.ilo.org/actemp/publications/WCMS_579554/lang--en/index.htm

30. Reese, B. (2019, January 1). *AI will create millions more jobs than it will destroy. Here's how.* Singularity Hub. https://singularityhub.com/2019/01/01/ai-will-create-millions-more-jobs-than-it-will-destroy-heres-how/

31. Azmuk, N.A. (2019). *Transformatsiia zainiatosti pry perekhodi do tsyfrovoi ekonomiky: hlobalni vyklyky ta stratehii adaptatsii [Transforming employment at the transition to the digital economy: global challenges and adaptation strategies]*. Znannia. https://iie.org.ua/monografiyi/transformacija-zajnjatosti-pri-perehodi-do-cifrovoi-ekonomiki-globalni-vikliki-ta-strategii-adaptacii/ [in Ukrainian].

32. Morrison, M. (2022, January 19). *History of SMART Objectives*. RapidBI. https://rapidbi.com/history-of-smart-objectives/

33. Novikova, O., Zaloznova, Yu., Amosha, O., Khandii, O., Azmuk, N., Ostafiichuk, Ya., Shamileva, L., Pankova O., Novak, I., Shastun, A., Kasperovych, O., Ishchenko, O., Krasulina, Ya., Amelicheva, L., & Kompaniiets, V. (2022). *Transformatsiia sotsialno-trudovoi sfery v umovakh tsyfrovizatsii ekonomiky [Transformation of the social and labor sphere in the conditions of digitalization of the economy]*. NAN Ukrainy, In-t ekonomiky prom-sti. https://iie.org.ua/monografiyi/transformacija-socialno-trudovoi-sferi-v-umovah-cifrovizacii-ekonomiki/ [in Ukrainian]

34. Kolot, A. M., & Herasymenko, O. O. (2021). *Pratsia XXI: filosofiia zmin, vyklyky, vektory rozvytku [Work XXI: philosophy of change, challenges, vectors of development]*. KNEU. https://ir.kneu.edu.ua/handle/2010/36870?show=full [in Ukrainian]

35. International Labour Organization. (2019). *Work for a brighter future – Global Commission on the Future of Work*. https://www.ilo.org/wcmsp5/groups/public/---dgreports/---cabinet/documents/publication/wcms_662410.pdf

36. Frey, C.B., Osborne, M. (2015). *Technology at work: The future of innovation and employment.* Citi Global Perspectives and Solutions. https://www.oxfordmartin.ox.ac.uk/downloads/reports/Citi_GPS_Technology_Work.pdf

37. Manyika, J., Chui, M, Miremadi, M., Bughin, J., George, K., Willmott, P., & Dewhurst, M. (2017, January 12). *A future that works: Automation, employment, and productivity*. McKinsey Global Institute. https://www.mckinsey.com/featured-insights/digital-disruption/harnessing-automation-for-a-future-that-works/de-DE

38. Organization for Economic Co-operation and Development. (2016). *Policy Brief on the Future of Work – Automation and independent work in a digital economy*. OECD Publishing. https://www.oecd.org/els/emp/Policy%20

brief%20-%20Automation%20and%20Independent%20Work%20in%20a%20Digital%20Economy.pdf

39. World Bank. (2016). *World Development Report 2016: Digital dividends*. https://doi.org/10.1596/978-1-4648-0671-1

40. World Economic Forum. (2018). *The Future of Jobs Report*. https://www3.weforum.org/docs/WEF_Future_of_Jobs_2018.pdf

41. United Nations, Department of Economic and Social Affairs, Population Division. (2017). *World Population Prospects: The 2017 revision, key findings and advance tables* (Working Paper No. ESA/P/WP/248). https://desapublications.un.org/publications/world-population-prospects-2017-revision

42. International Labour Organization. (1991-2021). *World Employment and Social Outlook Data Finder* [Data set]. Retrieved July 10, 2022, from https://www.ilo.org/wesodata

43. Kolot, A. M., & Herasymenko, O. O. (2019). Social and labor development in the XXI century: to the nature of global changes, new opportunities, limitations and challenges. *Demography and social economy, 1*(35), 97–125. [in Ukrainian]

44. Kohonen, T. (2001). *Self-Organizing Maps* (3rd ed.). Springer.

45. Kobets, V., & Novak, O. (2021). EU countries clustering for the state of food security using machine learning techniques. *Neuro-Fuzzy Modeling Techniques in Economics, 10*, 86-118. http://doi.org/10.33111/nfmte.2021.086

46. State Statistics Service of Ukraine. (2013-2020). *Statystychnyi zbirnyk «Pratsia Ukrainy» [Statistical collection "Labor of Ukraine"]* [Data set]. Retrieved January 7, 2022, from https://www.ukrstat.gov.ua/druk/publicat/Arhiv_u/11/Arch_pu_zb.htm

47. State Statistics Service of Ukraine. (2013-2020). *Statystychnyi zbirnyk «Natsionalni rakhunky Ukrainy» [Statistical collection "National accounts of Ukraine"]* [Data set]. Retrieved January 7, 2022, from https://www.ukrstat.gov.ua/druk/publicat/Arhiv_u/03/Arch_nr.htm

48. State Statistics Service of Ukraine. (2013-2020). *Tablytsia «vytraty-vypusk» Ukrainy u tsinakh spozhyvachiv [Ukraine's consumption-output table at consumer prices]* [Data set]. Retrieved January 7, 2022, from https://www.ukrstat.gov.ua/operativ/operativ2006/vvp/vitr_vip/vitr_u/arh_vitr_u.html

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ENTERPRISE STRATEGIES STRATIFICATION BASED ON THE FUZZY MATRIX APPROACH

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A stratification model of enterprise strategies on the basis of tools of fuzzy set theory and fuzzy matrix analysis was developed. Classic methods of strategic diagnostics of the company, fuzzy methods of multi-criteria evaluation (Fuzzy Extension of Simplified Best-Worst Method (Fuzzy SBWM) and Fuzzy SAW) and fuzzy matrices were used to achieve the goals set. The classic Quantitative Strategic Planning Matrix (QSPM) criteria were used to make a strategic choice. The developed model is based on defined term sets of expert linguistic assessments (8-level – for determining the importance of SWOT factors and 7-level – for evaluating strategic alternatives) with their subsequent conversion into fuzzy numbers with triangular membership functions. The Fuzzy SBWM was used to calculate the importance of SWOT factors for each area of analysis, and the Fuzzy SAW method was used to determine the fuzzy integral evaluations of strategic alternatives for these areas. Strategic alternatives were positioned in fuzzy matrices "O – T" and "S – W" using the α-section. Stratification of strategies is based on the superposition of fuzzy matrices and the application of production rules for the obtained integral fuzzy estimates of strategic alternatives. The framework has been developed in the Excel software application to carry out calculations according to this approach, which contains the following components: a block for entering linguistic expert information (for each direction of analysis and evaluation of strategic alternatives) and transforming these linguistic data into fuzzy numbers in a triangular form, a block for calculating factor weighting coefficients by best and worst approaches and their fuzzy integral values, a block for calculating fuzzy values of strategies in the directions of "opportunities-threats" and "strengths-weaknesses" at different values of α-section, a block of production rules for stratification of strategies to carry out calculations according to this approach. The methodical approach enables the top management of the enterprise to determine the weighting coefficients of the SWOT factors and identify the list of preferable strategic alternatives for implementation.

Keywords: *fuzzy set theory, fuzzy matrix analysis, linguistic variable, term set, strategy stratification, fuzzy SBWM, fuzzy SAW method*

JEL Classification: C51, C63, D04

Formulation of the problem

The deepening of crisis phenomena in the global and domestic economies, which is caused by the influence of various factors, primarily the long-lasting coronavirus pandemic and the military invasion of the Russian Federation in Ukraine, leads to significant changes in the operating conditions of enterprises, changes in the management paradigm, and even strategic imperatives in their activities. These conditions are characterised by an extremely high level of uncertainty, dynamism, and difficulty in forecasting, which necessitates the application of new scientifically grounded methodologies for analysis, evaluation, and consideration of trends to ensure adequate and timely responses to challenges generated by the external environment.

One of the most critical stages in the strategic process is the analysis of the developed strategic alternatives with their subsequent evaluation and selection of a strategy to be implemented at the company. Therefore, consideration of the possibilities of improving the toolkit for solving this problem by considering the vagueness and ambiguity of the input information is an utter priority.

Analysis of recent research and publications

A substantial number of studies have been conducted on the theoretical and methodological aspects of strategic planning of companies' activities, in particular, by such well-known scholars as: S. Abraham [1], I. Ansoff [4], F. David [8, 9], L. Fahey, R. Randall [12], K. Fleisher, B. Bensoussan [13], W. Glueck, L. Jauch [17], R. Grant [18], D. Hussey [23, 24], G. Johnson, K. Scholes, R. Whittington [26], Ph. Kotler, R. Berger, N. Bickhoff [28], J. Lampel, H. Mintzberg, J. Quinn, S. Ghoshal [32], S. Leleur [34], A. Thompson, A. Strickland [43], T. Wheelen, J. Hunger, A. Hoffman, C. Bamford [44] and others.

In the last decade, one of the most prospective areas of applied research in strategic management has been the use of methods and models of fuzzy set theory [45], which have a high degree of adaptability to expert data, are flexible enough and adequate to the input information. A large number of publications examine the problems of strategic management through the prism of applying classical tools in a fuzzy framework. Thus, in [37], a fuzzy QSPM model is suggested. The authors [25] use the Fuzzy ANP method to determine the internal dependence among the parameters of the SWOT model and calculate their importance to select the best strategies for a textile enterprise. A similar idea is used in the research [14], but the VIKOR method is used for ranking strategies. In [38], the classical QSPM model is used as the primary analysis tool, while fuzzy TOPSIS determines the priority of strategic alternatives.

In [16, 42], fuzzy additive weighting using the Fuzzy SAW method is applied for selecting a maintenance strategy. In [15], a hybrid model based on SWOT analysis and Fuzzy AHP is constructed, with criteria and sub-criteria for evaluation being determined through SWOT analysis, and the Fuzzy AHP method is used for evaluating and ranking internal and external factors affecting competition in the education sector. Strategic selection is based on synchronising strategies obtained from the IE matrix and strategies developed based on SWOT analysis. The author [30] selects a strategy for the university based on Fuzzy AHP.

In [5], a model for evaluating and selecting enterprise strategies based on a modification of the classical quantitative strategic planning matrix is developed, with fuzzy multi-criteria evaluation methods being used to achieve the set goals (Fuzzy AHP for calculating the importance of analysis directions and evaluation criteria, and Fuzzy SAW for determining fuzzy integral evaluations of strategic alternatives according to these directions and overall). In addition to traditional criteria for evaluating strategic alternatives, it is proposed to consider the potential ability to achieve defined strategic goals. Strategic alternatives are ranked based on the defuzzified values of the obtained integral fuzzy evaluations.

For selecting a company's marketing strategy, a Mamdani fuzzy inference system is applied in [27], while the fuzzy analytic network process (FANP) is used in the study [22], and VIKOR and Fuzzy AHP are applied in work [36]. To select an enterprise management strategy to ensure its financial stability, the problem of diagnosing bankruptcy was being solved using methods of fuzzy sets [29] and fuzzy logic [35].

However, despite the growing number of publications in the field of strategic planning using the theory of fuzzy sets and fuzzy logic, there are issues related to improving the existing methodological approaches to evaluating and selecting strategies for their implementation at the company.

The aim and tasks of the research

The article aims to analyse the current state of research on the problems of evaluation and selection of strategies in the strategic process and develop an approach to their stratification based on the Fuzzy Extension of Simplified Best-Worst Method (F-SBWM), superposition of the built fuzzy evaluation matrices and application of the developed productive rules to identify strategic alternatives belonging to the corresponding hierarchical groups.

Results

The problem of evaluating strategies and making other strategic choices is an essential element of strategic planning at the enterprise, as the cost of miscalculations at this stage can be extremely high. It is considered that choosing from alternative strategy options is the least structured of all the decisions made by managers.

As G. Day notes in [10], "an unsuccessful choice of strategic direction is very costly for the company: its limited financial resources are scattered, valuable time is wasted, and managers neglect other (promising) opportunities, as they try to compensate for the losses caused by the failed option". In the worst case, choosing the "wrong" strategy can even lead to the destruction of the organisation and bankruptcy of the enterprise. In the words of Professors W. Glueck and L. Jauch, evaluating a strategy is a process through which strategists determine the extent to which a strategy can achieve its goals [17].

It should be noted that the process of evaluating strategies in current conditions requires significant improvement of traditional (classical) methodological approaches and the development of new methods and tools, which is related to several reasons and trends, including:

1) a sharp increase in uncertainty, instability, dynamics, and turbulence in the operating environment of enterprises;

2) the increasing complexity of forecasting the future and the need to use the scenario approach and other modern predictive methods, and the need not just to predict or plan the company's activities but to make precise, thorough, multivariate current and future forecasting in constantly changing complex conditions;

3) reduction of the time interval of "reliable" forecasting and, accordingly, planning due to changes, events, and phenomena that bring elements of chaos, spontaneity, imbalance and disorder into the activities of organisations;

4) a large number of factors, parameters, variables, and criteria that need to be applied in the evaluation process;

5) the use of cutting-edge information technologies, expert systems, and strategic decision support systems, rapid, practical innovations that radically change the traditional paradigm of strategic management;

6) the focus of modern companies on constantly increasing the speed of bringing products to market, with a simultaneous trend of reducing product life cycles and their rapid replacement;

7) the transformation of methods, rules, and conditions of conducting business in each country and, accordingly, the intensification of competition, which necessitates constant monitoring of sales markets, and competitors' activities, studying their strategic behaviour, and modelling future development parameters.

It should be noted that the evaluation of the strategy can be carried out both at the stage of selecting strategies for implementation at the enterprise and when exercising control over the execution in case of necessary adjustments depending on the change in the influence of external factors or changes in internal factors. Accordingly, four main approaches are applied in the field of strategy evaluation (strategic alternatives) in strategic management [2]:

– goal-centred approach, in which two implementations are possible: a) retrospective (and current) assessment of the degree of achievement of pre-defined strategic goals; b) the use of a tool that allows assessing, through expert methods, the potential ability to achieve these strategic goals in the future, i.e., to obtain relevant predictive estimates of the future "performance" of strategies;

– the comparative approach compares the company, its strategy, and the effectiveness of its activities with similar companies;

– the improvement approach assesses how the strategy evolves and improves over time;

– the normative approach does not compare the developed strategy with a single, defined, theoretically ideal strategy (which does not exist), but as R. Rumelt claims, “instead, it assesses whether the developed strategy has characteristics typically associated with successful, effective strategies. This only points to general factors associated with success in the chosen field of activity and does not yet explain the differences in productivity between firms” [41].

From the analysis of the above approaches to evaluating strategies (strategic alternatives), two approaches – the goal-centred (which allows assessing the potential ability to achieve goals) and the normative approach can be applied to evaluate the long-term advantages of the strategy and strategic choice (Fig. 1).

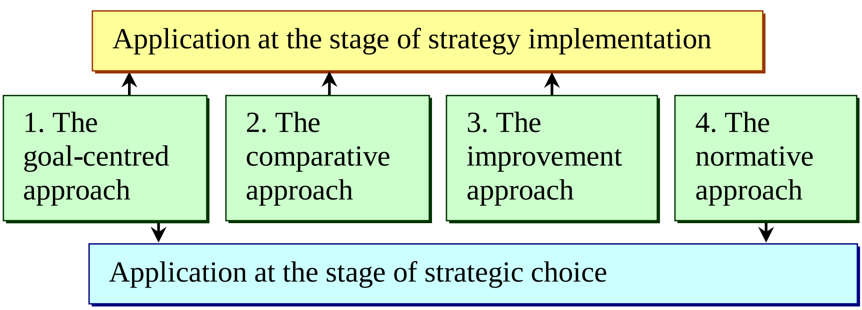

Fig. 1. Application of methodological approaches to strategy evaluation at the stages of the strategic process

It should be noted that the normative approach focuses on critical factors that affect the future situation and relies on a specific type of rational logic for conducting the evaluation. Goal-centred approach with retrospective evaluation of the degree of its achievement, comparative and improvement approaches are more focused on measuring business efficiency, strategy performance, which is being implemented, and which can be directly observed and are essential for operational reasons. In this study, the emphasis will be on evaluating strategic alternatives to select them for implementation in the enterprise.

Let us consider some meaningful relationships and statements of fuzzy set theory that will be necessary when addressing the tasks of this study.

In this paper, a triangular representation of a fuzzy number will be used $\tilde{A} = (a_1;\, a_2;\, a_3)$ (Fig. 2) with corresponding membership function (1).

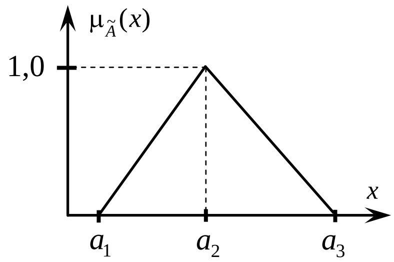

Fig. 2. Graphical representation of a fuzzy number with a triangular membership function

$$\mu_{\tilde{A}}(x) = \begin{cases} 0, \; x < a_1; \\ \dfrac{x - a_1}{a_2 - a_1}, \; x \in [a_1;\, a_2]; \\ \dfrac{x - a_3}{a_2 - a_3}, \; x \in [a_2;\, a_3]; \\ 0, \; x > a_3. \end{cases} \tag{1}$$

Note that if $\tilde{A} = (a_1;\, a_2;\, a_3)$ and $\tilde{B} = (b_1;\, b_2;\, b_3)$ – fuzzy numbers, then:

$$\tilde{A} \oplus \tilde{B} = (a_1;\, a_2;\, a_3) \oplus (b_1;\, b_2;\, b_3) = (a_1 + b_1;\, a_2 + b_2;\, a_3 + b_3)\,, \tag{2}$$

$$\tilde{A} (-) \tilde{B} = (a_1;\, a_2;\, a_3)(-)(b_1;\, b_2;\, b_3) = (a_1 - b_3;\, a_2 - b_2;\, a_3 - b_1)\,, \tag{3}$$

$$\tilde{A} \otimes \tilde{B} = (a_1;\, a_2;\, a_3) \otimes (b_1;\, b_2;\, b_3) = (a_1 \times b_1;\, a_2 \times b_2;\, a_3 \times b_3)\,, \tag{4}$$

$$\tilde{A} (\div) \tilde{B} = (a_1;\, a_2;\, a_3)(\div)(b_1;\, b_2;\, b_3) = (a_1 / b_3;\, a_2 / b_2;\, a_3 / b_1)\,, \tag{5}$$

$$c \times \tilde{A} = c \times (a_1;\, a_2;\, a_3) = (ca_1;\, ca_2;\, ca_3),\ c \ge 0,\ \ c\ -\ const, \tag{6}$$

$$c \times \tilde{A} = c \times (a_1;\, a_2;\, a_3) = (ca_3;\, ca_2;\, ca_1),\ c < 0,\ \ c\ -\ const. \tag{7}$$

If $\tilde{A}_i = (a_{1i};\, a_{2i};\, a_{3i})$, $i = \overline{1,\ n}$, then

$$\bigoplus_{i=1}^{n} \tilde{A}_i = \bigoplus_{i=1}^{n} (a_{1i};\, a_{2i};\, a_{3i}) = \left(\sum_{i=1}^{n} a_{1i};\, \sum_{i=1}^{n} a_{2i};\, \sum_{i=1}^{n} a_{3i} \right). \tag{8}$$

By [33], the COA (Center of Area) method (9) is used for the defuzzification of a fuzzy triangular number $\tilde{A} = (a_1;\, a_2;\, a_3)$:

$$\tilde{A}^{def} = \frac{(a_3 - a_1) + (a_2 - a_1)}{3} + a_1. \tag{9}$$

To implement this model, the author proposes a methodological approach based on the fuzzy set theory [45], the main stages of which are shown in Fig. 3.

At **stage 1**, the enterprise and strategic analysts thoroughly diagnose the it and its environment using appropriate tools (EFE and IFE matrices, ETOM method, PEST analysis, SWOT analysis, competitive analysis methods, etc.).

Stage 2 – formation of a working group of experts with professional knowledge, experience and authority. Including external experts with relevant competencies in the problem area and qualifications is also advisable.

Stage 3 is a crucial part of the strategic process because it enables the creation of a list of strategic options utilising traditional planning tools (correlation SWOT analysis, portfolio analysis matrices – Ansoff, IEM, BCG, GE-McKinsey, SPACE), and their modification based on fuzzy methodology. As G. Day notes, "... the best strategic choice is made when decision-makers are looking for and discussing several alternatives at the same time. Diversity gives managers a basis for comparison and boosts creativity by offering combinations of different strategies" [10].

We denote the strategic alternatives obtained for evaluation $s = \{s_1;\, s_2;\, ...;\, s_n\}$, where n – their number.

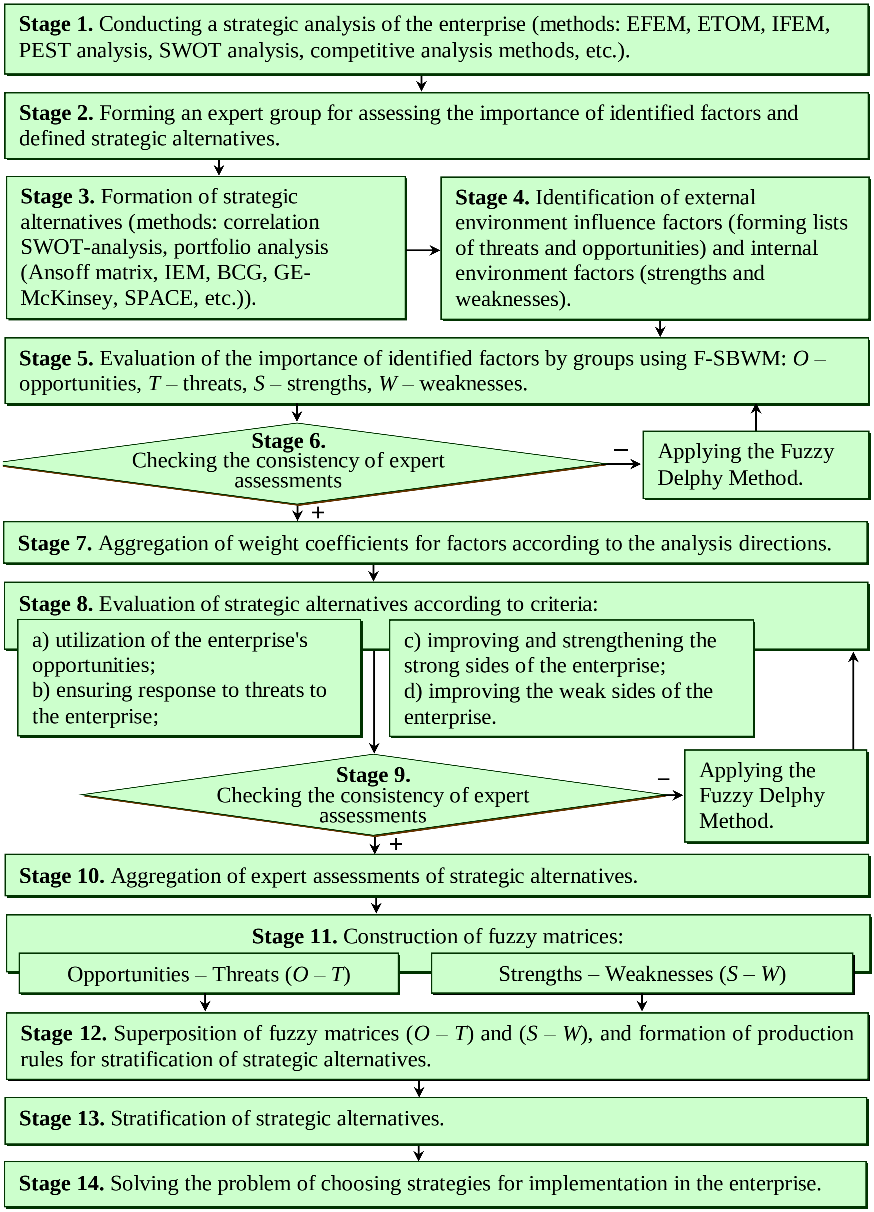

Fig. 3. Stages of stratification of strategic alternatives for the enterprise

During implementation of **Stage 4**, it is supposed to identify the criteria for evaluating the formed strategic alternatives. This is one of the most challenging moments in the analysis procedure and the choice of a strategy for implementation since the choice of a system of evaluation criteria depends on many factors, in particular, on the sectoral affiliation of the enterprise, the level of competition in the industry, the size and competitive position of the enterprise, etc. As G. Day [10] notes, “the debate over which alternatives to choose will only be productive when the alternatives are compared in terms of the strategic pillars that underlie shareholder value creation.”

In the literature, there is a serious controversy on the requirements or criteria for evaluating strategies. In particular, G. Day [10] suggests checking each strategic alternative using the following tests:

– test 1: How attractive is the market opportunity?

– test 2: How sustainable is the competitive advantage?

– test 3: What are the prospects for successful implementation?

– test 4: Are the risks acceptable?

– test 5: Will the forecast financial results be achieved and increase shareholder value?

D. Hussey [24], based on practical experience, identified several questions, the answers to which can make it possible to check whether there are elementary errors in the strategy:

– is the strategy identified and clearly stated?
– has it considered competitors and the industry structure?
– does it match the realities of the market?
– is the geographical scope appropriate?
– is it consistent with environmental forces?
– are the levels of risk acceptable?
– does it enhance shareholder value?
– does it match corporate competence and resources?
– does it match the company culture?
– does it have an appropriate time horizon?
– does the plan have internal consistency?

The authors [43] suggest considering the following criteria for choosing a strategy:

1) *Compliance with the environment*. The strategy must comply with the conditions of competition, market opportunities and threats, and other aspects of the external environment. At the same time, the

strategy should also consider the company's strengths and weaknesses, its competence, and competitive opportunities. A strategy must match the internal and external environments to achieve the desired results.

2) *Competitive advantage*. The strategy must provide a sustainable competitive advantage. The greater the competitive advantage the strategy provides, the higher the efficiency and return.

3) *Efficiency*. The better strategy choice is confirmed by improving two parameters – profitability and strengthening the competitive and market position.

According to the views of Ph. Kotler and his colleagues [28], in order to solve various problems, a strategy must meet five basic requirements:

– integration (the strategy should include all areas and activities of the company);

– awareness (the person making a strategic decision must act consciously and intentionally);

– action orientation;

– methodicity (third parties must understand the strategy);

– its goal is not only to solve complex tasks but also to achieve long-term success.

R. Rumelt [41] proposed a system of criteria for evaluating strategies, which contains the following requirements:

– consistency: the strategy must not present mutually inconsistent goals and policies;

– consonance: the strategy must represent an adaptive response to the external environment and to the critical changes occurring within it;

– advantage: the strategy must provide for the creation and/or maintenance of a competitive advantage in the selected area of activity;

– feasibility: the strategy must neither overtax available resources nor create unsolvable sub problems.

The authors [31] proposes that during strategic decision-making, strategic alternatives should be analysed through four interconnected lenses: financial, market, competitive advantage, and operating model. G. Johnson, K. Scholes and R. Whittington [26] propose three universal evaluation criteria, each of which is decomposed into a series of questions through decomposition:

1. Suitability – can be assessed by the degree of its correspondence to the needs identified during the strategic analysis. Such a suitability

test is sometimes viewed as a test for adequacy to external environmental factors and organisational resources, as well as for consistency with organisational goals:

a) the strategy should solve a strategic problem or implement the opportunities identified during the strategic analysis;

b) the strategy must correspond to the goals of the organisation, both financial and non-financial performance indicators of the organisation;

c) the strategy must correspond to the state and requirements of the environment. It is checked to what extent the strategy is related to the requirements of the main subjects of the environment, to what extent the factors of market dynamics and the dynamics of the development of the product life cycle are taken into account, whether the implementation of the strategy will lead to the emergence of new competitive advantages, etc.;

d) the strategy should be based on appropriate organisational resources and capabilities and consider their potential in using external opportunities. In this case, it is evaluated to what extent the chosen strategy is related to other strategies, whether the strategy corresponds to the capabilities of the staff, whether the existing structure enables the successful implementation of the strategy, whether the strategy implementation program is verified, etc.

2. Feasibility of the proposed strategy – involves analysing the strategy in terms of how well it works in practice and how difficult it is to implement. In the evaluation process, it is necessary to answer the following questions:

a) are there enough resources to implement this strategy?

b) can the company achieve the required level of operational indicators, for example, in terms of quality or level of service provision? Will a strategy aimed at reducing costs lead to such negative consequences as a lack of experienced management personnel and qualified employees, an outdated technological process or product;

c) how will competitors react, and how will the organisation respond to their actions?

3. The acceptability of the proposed strategy is an assessment of the potential perception by stakeholders of the expected results of the implementation of this strategy, such as risk, profit, reward, ethics, and the impact of the relations of the parties. The following questions are offered for such a test:

a) what will be the financial efficiency of the company? What is the ratio of costs and benefits from the activity? Is there an unacceptable risk to the company's overall liquidity or capital structure?

b) is there a risk of unacceptable deterioration of the company's relations with its stakeholders? Will the proposed strategy alienate employees, shareholders, existing customers, or government entities?

c) what will be the impact of the proposed strategy on internal systems and processes? Even if the strategy seems feasible, will it not be a source of additional stress for the company's employees?

The three mentioned above strategies evaluation criteria are a set of primary tools for making strategic choices. They encourage managers to openly discuss the implications of proposed strategies and even assess the degree of risk and uncertainty associated with them. These criteria make it possible to assess the acceptability of the strategy for stakeholders. However, the developed strategy may only be helpful if the organisation creates a mechanism for its implementation. This is a separate big problem, which includes building adequate strategies of organisational structures, financing functional strategies, selecting managers with leadership qualities, and creating a corporate culture that enables all employees to reveal their qualities better.

According to S. Abraham [1], regardless of the process used to generate strategic alternatives, each resulting alternative must be rigorously evaluated in terms of its ability to meet four criteria:

1. Mutual exclusivity: doing any one alternative would preclude doing any other.
2. Success: it must be feasible and have a good probability of success.
3. Completeness: it must take into account all the key strategic issues.
4. Internal consistency: it must make sense on its own as a strategic decision for the entire firm and not contradict key goals, policies, and strategies currently being pursued by the firm or its units.

Other criteria can be used besides the above: complete coverage of all critical aspects of the activity, degree of risk, etc.

In this study, the criteria of the classic quantitative strategic planning matrix (Quantitative Strategic Planning Matrix – QSPM) [9] are used to make a strategic choice. It should be noted that in it, the assessment of the priority of strategic alternatives is carried out in two directions: external – how effectively the company's strategies use existing opportunities and minimise the possible negative consequences of threats generated by the external environment, and internal – determining the level of "strategy influence" on improving the internal state of the enterprise or its strategic business units, i.e. to what extent this strategy allows to "strengthen" its strengths and improve its weaknesses [5].

In accordance with this, factors of the external environment that significantly affect the enterprise are determined – favourable opportunities $F^O = \{F_1^O; F_2^O; ...; F_{m^O}^O\}$ and threats $F^T = \{F_1^T; F_2^T; ...; F_{m^T}^T\}$, and essential factors of the internal environment – strengths $F^S = \{F_1^S; F_2^S; ...; F_{m^S}^S\}$ and weaknesses $F^W = \{F_1^W; F_2^W; ...; F_{m^W}^W\}$, moreover $m^O; m^T; m^S; m^W$ – the number of factors identified by the directions of analysis *O*, *T*, *S*, *W*, respectively.

For example, for a domestic enterprise operating in the regional market to produce and sell food products, the identified lists of these factors are given in the Tables 1 and 2.

Table 1

CRITICAL INTERNAL SUCCESS FACTORS OF THE ENTERPRISE

	List of critical internal success factors of the enterprise
Strengths	F_1^S – availability of raw materials and availability of resources; F_2^S – high level of management; F_3^S – high level of business reputation; F_4^S – a wide range of products; F_5^S – modern production technologies; F_6^S – powerful advertising support; F_7^S – compliance of the company's products with standards and environmental regulations; F_8^S – high-quality products.
Weaknesses	F_1^W – a depreciation of fixed assets; F_2^W – insufficiently high qualification of personnel; F_3^W – little experience in the market; F_4^W – the level of marketing is not high enough; F_5^W – low consumer commitment; F_6^W – low level of strategic flexibility; F_7^W – the unstable financial condition of the company; F_8^W – insufficient funds for the implementation of innovative projects.

Table 2

CRITICAL EXTERNAL FACTORS INFLUENCING THE ENTERPRISE

	List of critical external success factors of the enterprise
Opportunities	F_1^O – consumer attachment to domestic food products; F_2^O – availability of raw material suppliers; F_3^O – development of unique production technologies; F_4^O – expansion of the sales network; F_5^O – access to international markets; F_6^O – introduction of stricter requirements for product quality control.
Threats	F_1^T – strengthening and intensifying the level of competition; F_2^T – decline in the purchasing power of buyers; F_3^T – a price increase of products; F_4^T – capacity building by competitors; F_5^T – increase in the inflation rate; F_6^T – dependence of raw material prices on natural conditions.

Stage 5. To evaluate the importance of the identified factors by groups: O – opportunities, T – threats, S – strengths, W – weaknesses, we will use the Fuzzy Extension of the Simplified Best-Worst Method (Fuzzy SBWM) [3, 11]. BWM was proposed by J. Rezaei [39, 40] for multi-criteria decision-making problems based on pairwise comparisons. In [20] and [21] this method was extended for the theory of fuzzy sets mainly using triangular fuzzy numbers and in [19] – for group decision-making.

The illustration of its application for a set of factors in the general case is provided $F = \{F_1 ; F_2 ; ...; F_m\}$. It should be noted that the Fuzzy SBWM procedure involves the use of two approaches: the "best" approach and the "worst" approach, the results of which are combined to determine the integral values of the importance of the studied factors (Fig. 4).

Step 1. Determination of the most important ("best") and least important ("worst") factors for each direction of analysis should be carried out based on reaching a consensus by a group of experts. In the general case they are denoted as follows: F_{best} and F_{worst}.

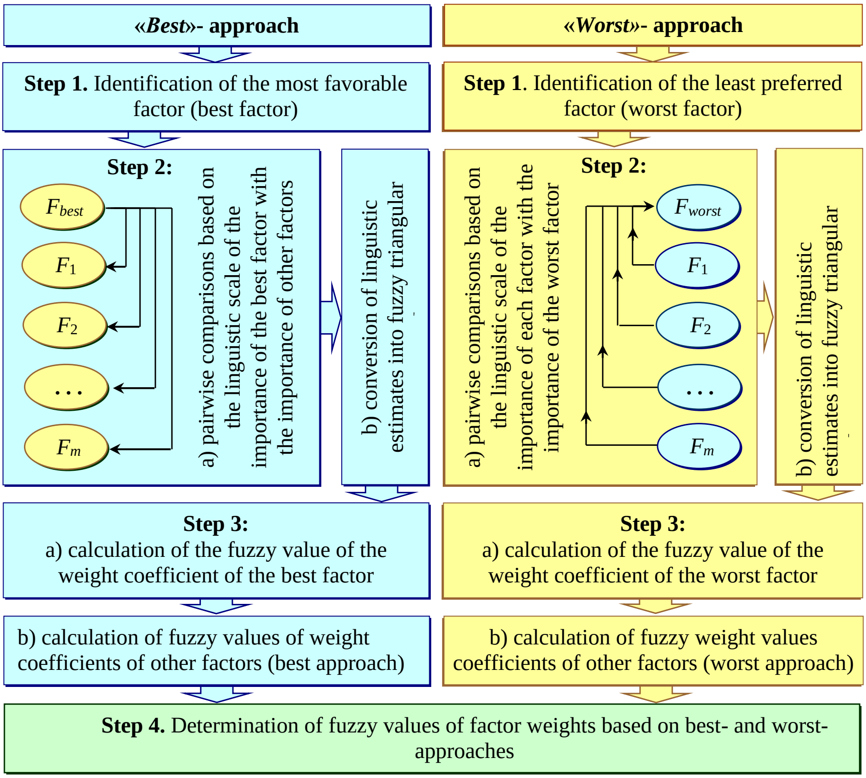

Fig. 4. Scheme of application of the F-SBWM method for determining importance weight coefficients of SWOT factors

Step 2. The first consideration is the "best" approach, which is proceeded with the following steps:

a) linguistic evaluation by each of K experts of the importance (priority) of the "best" factor compared to each of the other factors using the terms listed in the Table 3. This will result in linguistic assessments L_{jk}^{best} ($j=\overline{1,\ m}$, $k=\overline{1,\ K}$);

b) transfer of received grades L_{jk}^{best} into the corresponding fuzzy triangular numbers (Fig. 5) according to the scale of the Table 3 in the form: $\tilde{a}_{jk}^{best}=(\alpha_{jk}^{best};\ \beta_{jk}^{best};\ \gamma_{jk}^{best})$, $j=\overline{1,\ m}$, $k=\overline{1,\ K}$.

Table 3

LINGUISTIC TERMS FOR ASSESSING THE IMPORTANCE OF FACTORS AND CORRESPONDING FUZZY NUMBERS IN THE TRIANGULAR FORM [39]

Linguistic terms for evaluating the importance of factors	Marking	Fuzzy form
Equally	EI	(1; 1; 1)
Weakly	WI	(1; 2; 3)
Moderate	MI	(2; 3; 4)
Moderate plus	MP	(3; 4; 5)
Strong	SI	(4; 5; 6)
Strong plus	SP	(5; 6; 7)
Very strong	VS	(6; 7; 8)
Extreme	EX	(7; 8; 9)

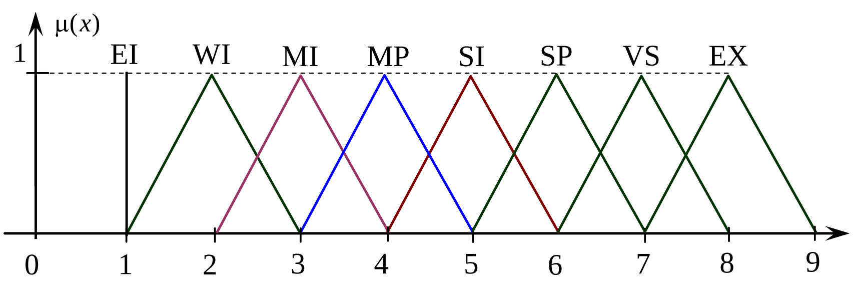

Fig. 5. Membership functions for linguistic terms [39]

The "worst" approach in **step 2** is carried out by the way:

a) linguistic evaluation by each of K experts of the importance (priority) of each of the factors compared to the least important factor (worst factor) using the terms listed in the Table 3 (result: L_{jk}^{worst}, $j=\overline{1,\ m}$; $k=\overline{1,\ K}$) and

b) transfer of received grades L_{jk}^{worst} into corresponding fuzzy triangular numbers according to the scale of the Table 3 in the form $\tilde{a}_{jk}^{worst}=(\alpha_{jk}^{worst};\ \beta_{jk}^{worst};\ \gamma_{jk}^{worst})$, $j=\overline{1,\ m}$, $k=\overline{1,\ K}$.

Step 3 calculates the fuzzy importance values of each factor of the "best" approach in the form $\tilde{w}_{jk}^{best} = (x_{jk}^{best}; y_{jk}^{best}; z_{jk}^{best})$, $j = \overline{1,\ m}$, $k = \overline{1,\ K}$.

To do this:

a) the importance (priority) of the "best" factor $\tilde{w}_{Bk}^{best}$ is first calculated using equation (10):

$$\left(\bigoplus_{j=1}^{m} \frac{1}{\tilde{a}_{jk}^{best}} \right) \otimes \tilde{w}_{Bk}^{best} = 1,\ k = \overline{1,\ K}. \tag{10}$$

From here

$$\tilde{w}_{Bk}^{best} = \frac{1}{\bigoplus_{j=1}^{m} \frac{1}{\tilde{a}_{jk}^{best}}} =$$

$$= \frac{1}{\frac{1}{(\alpha_{1k}^{best}; \beta_{1k}^{best}; \gamma_{1k}^{best})} \oplus \frac{1}{(\alpha_{2k}^{best}; \beta_{2k}^{best}; \gamma_{2k}^{best})} \oplus \ldots \oplus \frac{1}{(\alpha_{mk}^{best}; \beta_{mk}^{best}; \gamma_{mk}^{best})}} =$$

$$= \frac{1}{\left(\frac{1}{\gamma_{1k}^{best}}; \frac{1}{\beta_{1k}^{best}}; \frac{1}{\alpha_{1k}^{best}} \right) \oplus \left(\frac{1}{\gamma_{2k}^{best}}; \frac{1}{\beta_{2k}^{best}}; \frac{1}{\alpha_{2k}^{best}} \right) \oplus \ldots \oplus \left(\frac{1}{\gamma_{mk}^{best}}; \frac{1}{\beta_{mk}^{best}}; \frac{1}{\alpha_{mk}^{best}} \right)} =$$

$$= \frac{1}{\left(\sum_{j=1}^{m} \frac{1}{\gamma_{jk}^{best}}; \sum_{j=1}^{m} \frac{1}{\beta_{jk}^{best}}; \sum_{j=1}^{m} \frac{1}{\alpha_{jk}^{best}} \right)} = \left(\frac{1}{\sum_{j=1}^{m} \frac{1}{\alpha_{jk}^{best}}}; \frac{1}{\sum_{j=1}^{m} \frac{1}{\beta_{jk}^{best}}}; \frac{1}{\sum_{j=1}^{m} \frac{1}{\gamma_{jk}^{best}}} \right) =$$

$$= (x_{Bk}^{best}; y_{Bk}^{best}; z_{Bk}^{best}),\ k = \overline{1,\ K}. \tag{11}$$

b) further, since ratios must be satisfied

$$\tilde{w}_{Bk}^{best} (-) \tilde{a}_{jk}^{best} \otimes \tilde{w}_{jk}^{best} = 0, \tag{12}$$

then for arbitrary $j=\overline{1,\ m}$

$$w_{jk}^{best}=\frac{\tilde{w}_{Bk}}{\tilde{a}_{jk}^{best}}=\frac{(x_{Bk}^{best};y_{Bk}^{best};z_{Bk}^{best})}{(\alpha_{jk}^{best};\ \beta_{jk}^{best};\ \gamma_{jk}^{best})}=$$

$$=\left(\frac{x_{Bk}^{best}}{\gamma_{jk}^{best}};\frac{y_{Bk}^{best}}{\beta_{jk}^{best}};\frac{z_{Bk}^{best}}{\alpha_{jk}^{best}}\right)=(x_{jk}^{best};y_{jk}^{best};z_{jk}^{best}). \qquad (13)$$

For the “worst” approach in **step 3** the fuzzy importance values of each factor in the form $\tilde{w}_{jk}^{worst}=(x_{jk}^{worst};y_{jk}^{worst};z_{jk}^{worst})$, $j=\overline{1,\ m}$, $k=\overline{1,\ K}$, are calculated. For this:

a) first, the importance $\tilde{w}_{Wk}^{worst}$ of the “worst” factor is calculated from the equation:

$$\left(\bigoplus_{j=1}^{m}\tilde{a}_{jk}^{worst}\right)\otimes\tilde{w}_{Wk}^{worst}=1,\ k=\overline{1,\ K}. \qquad (14)$$

So,

$$\tilde{w}_{Wk}^{worst}=\frac{1}{\bigoplus_{j=1}^{m}\tilde{a}_{jk}^{worst}}=$$

$$=\frac{1}{(\alpha_{1k}^{worst};\beta_{1k}^{worst};\gamma_{1k}^{worst})\oplus(\alpha_{2k}^{worst};\beta_{2k}^{worst};\gamma_{2k}^{worst})\oplus\ldots\oplus(\alpha_{mk}^{worst};\beta_{mk}^{worst};\gamma_{mk}^{worst})}=$$

$$=\frac{1}{\left(\sum_{j=1}^{m}\alpha_{jk}^{worst};\ \sum_{j=1}^{m}\beta_{jk}^{worst};\sum_{j=1}^{m}\gamma_{jk}^{worst}\right)}=\left(\frac{1}{\sum_{j=1}^{m}\gamma_{jk}^{worst}};\ \frac{1}{\sum_{j=1}^{m}\beta_{jk}^{worst}};\frac{1}{\sum_{j=1}^{m}\alpha_{jk}^{worst}}\right)=$$

$$=(x_{Wk}^{worst};y_{Wk}^{worst};z_{Wk}^{worst}),\ k=\overline{1,\ K}. \qquad (15)$$

b) further, by substituting the weighting factor of the least important factor (15) into equation (16), it is possible to calculate the weighting factors of other factors (17).

$$\tilde{w}_{jk}^{worst}(-)\tilde{a}_{jk}^{worst}\otimes\tilde{w}_{Wk}^{worst}=0\text{, for arbitrary } j=\overline{1,m}. \qquad (16)$$

$$\tilde{w}_{jk}^{worst}=\tilde{a}_{jk}^{worst}\otimes\tilde{w}_{Wk}^{worst}=(\alpha_{jk}^{worst};\beta_{jk}^{worst};\gamma_{jk}^{worst})\otimes(x_{Wk}^{worst};y_{Wk}^{worst};z_{Wk}^{worst})=$$
$$=(\alpha_{jk}^{worst}x_{Wk}^{worst};\beta_{jk}^{worst}y_{Wk}^{worst};\gamma_{jk}^{worst}z_{Wk}^{worst})=(x_{jk}^{worst};y_{jk}^{worst};z_{jk}^{worst}). \qquad (17)$$

Step 4. Fuzzy values of factor weighting coefficients are calculated as the arithmetic mean of fuzzy values of weighting coefficients obtained based on the best and worst approaches:

$$\tilde{w}_{jk}=\frac{1}{2}(\tilde{w}_{jk}^{best}+\tilde{w}_{jk}^{worst})=\frac{1}{2}((x_{jk}^{best};y_{jk}^{best};z_{jk}^{best})\oplus(x_{jk}^{worst};y_{jk}^{worst};z_{jk}^{worst}))=$$
$$=\left(\frac{1}{2}(x_{jk}^{best}+x_{jk}^{worst});\ \frac{1}{2}(y_{jk}^{best}+y_{jk}^{worst});\ \frac{1}{2}(z_{jk}^{best}+z_{jk}^{worst})\right)=$$
$$=(x_{jk};y_{jk};z_{jk}). \qquad (18)$$

To check the consistency of the evaluations of each expert, the coefficient CR_k can be used, which is calculated from the ratio:

$$CR_k=def\left(\bigoplus_{j=1}^{m}(\tilde{w}_{jk}^{best}(-)\tilde{w}_{jk}^{worst})^2\right), \qquad (19)$$

or the total deviation coefficient according to formula [3]:

$$TD_k=def\left(\bigoplus_{j=1}^{m}\left(\left(\tilde{a}_{jk}^{best}(-)\frac{\tilde{w}_{Bk}^{best}}{\tilde{w}_{jk}}\right)^2\oplus\left(\tilde{a}_{jk}^{worst}(-)\frac{\tilde{w}_{jk}}{\tilde{w}_{Wk}^{worst}}\right)^2\right)\right). \qquad (20)$$

If the values of the calculated coefficients are significant enough, experts need to revise their estimates of superiority in pairwise comparisons to reach an acceptable range for these coefficients.

The weighting coefficients of the factors by directions are denoted, that are calculated based on the estimates of each expert *O*, *T*, *S*, *W* in accordance:

$$\tilde{w}_{jk}^{O} = (x_{jk}^{O}; y_{jk}^{O}; z_{jk}^{O}),\ \tilde{w}_{jk}^{T} = (x_{jk}^{T}; y_{jk}^{T}; z_{jk}^{T}),$$
$$\tilde{w}_{jk}^{S} = (x_{jk}^{S}; y_{jk}^{S}; z_{jk}^{S}),\ \tilde{w}_{jk}^{W} = (x_{jk}^{W}; y_{jk}^{W}; z_{jk}^{W}).$$

At stage 6, the group consistency of experts' assessments is checked based on the calculation of concordance coefficients for each area of analysis. In the case of a significant difference between these estimates, the fuzzy Delphi method [7] can be applied.

Stage 7. In the case of satisfactory consistency of experts' assessments, the aggregation of factor weights is carried out according to the following formulas:

$$\tilde{w}_{j}^{O} = \frac{1}{K}\bigoplus_{k=1}^{K}\tilde{w}_{jk}^{O} = \frac{1}{K}\bigoplus_{k=1}^{K}(x_{jk}^{O}; y_{jk}^{O}; z_{jk}^{O}) = (x_{j}^{O}; y_{j}^{O}; z_{j}^{O}), \quad j = \overline{1, m^{O}}; \tag{21}$$

$$\tilde{w}_{j}^{T} = \frac{1}{K}\bigoplus_{k=1}^{K}\tilde{w}_{jk}^{T} = \frac{1}{K}\bigoplus_{k=1}^{K}(x_{jk}^{T}; y_{jk}^{T}; z_{jk}^{T}) = (x_{j}^{T}; y_{j}^{T}; z_{j}^{T}), \quad j = \overline{1, m^{T}}; \tag{22}$$

$$\tilde{w}_{j}^{S} = \frac{1}{K}\bigoplus_{k=1}^{K}\tilde{w}_{jk}^{S} = \frac{1}{K}\bigoplus_{k=1}^{K}(x_{jk}^{S}; y_{jk}^{S}; z_{jk}^{S}) = (x_{j}^{S}; y_{j}^{S}; z_{j}^{S}), \quad j = \overline{1, m^{S}}; \tag{23}$$

$$\tilde{w}_{j}^{W} = \frac{1}{K}\bigoplus_{k=1}^{K}\tilde{w}_{jk}^{W} = \frac{1}{K}\bigoplus_{k=1}^{K}(x_{jk}^{W}; y_{jk}^{W}; z_{jk}^{W}) = (x_{j}^{W}; y_{j}^{W}; z_{j}^{W}), \quad j = \overline{1, m^{W}}. \tag{24}$$

For further application of the received values of the weighting coefficients of the factors by directions *O*, *T*, *S*, *W* the defuzzified by formula (9) values $(\tilde{w}_{j}^{O})^{def}$, $(\tilde{w}_{j}^{T})^{def}$, $(\tilde{w}_{j}^{S})^{def}$, $(\tilde{w}_{j}^{W})^{def}$ can be used.

At stage 8, the strategic alternatives determined at stage 3 are evaluated s_i, $i = \overline{1, n}$, according to the criteria, which are SWOT factors:

a) to what extent it enables the enterprise to use opportunities (F_1^O; F_2^O; ...; $F_{m^O}^O$) generated by the external environment;

b) to what extent it makes it possible to respond to threats and reduce their impact (F_1^T; F_2^T; ...; $F_{m^T}^T$) on the enterprise;

c) to what extent it contributes to the improvement and further consolidation of existing strengths (F_1^S; F_2^S; ...; $F_{m^S}^S$) for the enterprise;

d) to what extent it enables the elimination of weaknesses (F_1^W; F_2^W; ...; $F_{m^w}^W$) for the enterprise.

For evaluating the level of strategic alternatives s_i, $i=\overline{1,n}$, according to SWOT criteria, the following set of terms is used: $TS=\{$Extremely Low (EL), Very Low (VL); Low (L); Medium (M); High (H); Very High (VH), Extremely High (EH)$\}$.

Fuzzy numbers give the semantics of terms on the interval $[0;6]$ (Fig. 6) with corresponding membership functions and fuzzy numbers in triangular representation: EL: $(0;0;1)$; VL: $(0;1;2)$; L: $(1;2;3)$; M: $(2;3;4)$; H: $(3;4;5)$; VH: $(4;5;6)$; EH: $(5;6;6)$.

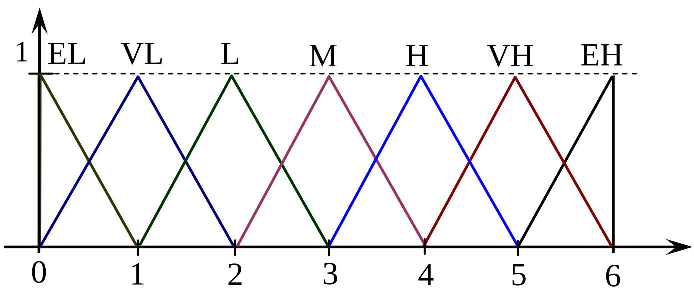

Fig. 6. Membership functions of the terms of assessment the level of strategic alternatives

So, L_{ijk}^O, L_{ijk}^T, L_{ijk}^S, L_{ijk}^W are the linguistic evaluations by the k-th expert of the i-th strategic alternative according to the j-factor of the corresponding direction of analysis.

Estimates are transformed using a triangular form of representation:

$$L_{ijk}^O \to \tilde{O}_{ijk} = (O_{ijk}^{\alpha}; O_{ijk}^{\beta}; O_{ijk}^{\gamma});$$

$$L_{ijk}^T \to \tilde{T}_{ijk} = (T_{ijk}^{\alpha}; T_{ijk}^{\beta}; T_{ijk}^{\gamma});$$

$$L_{ijk}^S \to \tilde{S}_{ijk} = (S_{ijk}^{\alpha}; S_{ijk}^{\beta}; S_{ijk}^{\gamma});$$

$$L_{ijk}^W \to \tilde{W}_{ijk} = (W_{ijk}^{\alpha}; W_{ijk}^{\beta}; W_{ijk}^{\gamma}).$$

Stage 9 checks the group consistency of expert evaluations of strategic alternatives based on calculating concordance coefficients for each line of analysis. If necessary, as in stage 6, the procedure of the Fuzzy Delphi method can be applied.

Stage 10. Aggregation of the obtained fuzzy estimates of experts is carried out according to the following formulas:

$$\tilde{O}_{ij} = \frac{1}{K}\bigoplus_{k=1}^{K}\tilde{O}_{ijk} = \left(\frac{1}{K}\sum_{k=1}^{K}O_{ijk}^{\alpha};\frac{1}{K}\sum_{k=1}^{K}O_{ijk}^{\beta};\frac{1}{K}\sum_{k=1}^{K}O_{ijk}^{\gamma}\right); \tag{25}$$

$$\tilde{T}_{ij} = \frac{1}{K}\bigoplus_{k=1}^{K}\tilde{T}_{ijk} = \left(\frac{1}{K}\sum_{k=1}^{K}T_{ijk}^{\alpha};\frac{1}{K}\sum_{k=1}^{K}T_{ijk}^{\beta};\frac{1}{K}\sum_{k=1}^{K}T_{ijk}^{\gamma}\right); \tag{26}$$

$$\tilde{S}_{ij} = \frac{1}{K}\bigoplus_{k=1}^{K}\tilde{S}_{ijk} = \left(\frac{1}{K}\sum_{k=1}^{K}S_{ijk}^{\alpha};\frac{1}{K}\sum_{k=1}^{K}S_{ijk}^{\beta};\frac{1}{K}\sum_{k=1}^{K}S_{ijk}^{\gamma}\right); \tag{27}$$

$$\tilde{W}_{ij} = \frac{1}{K}\bigoplus_{k=1}^{K}\tilde{W}_{ijk} = \left(\frac{1}{K}\sum_{k=1}^{K}W_{ijk}^{\alpha};\frac{1}{K}\sum_{k=1}^{K}W_{ijk}^{\beta};\frac{1}{K}\sum_{k=1}^{K}W_{ijk}^{\gamma}\right). \tag{28}$$

Next, using the Fuzzy SAW method, the integral values of strategic alternatives for each direction of analysis are calculated:

$$\tilde{O}_{i} = \bigoplus_{j=1}^{m^O}\tilde{w}_j^{O}\otimes\tilde{O}_{ij} = (O_i^{\alpha};O_i^{\beta};O_i^{\gamma}); \tag{29}$$

$$\tilde{T}_{i} = \bigoplus_{j=1}^{m^T}\tilde{w}_j^{T}\otimes\tilde{T}_{ij} = (T_i^{\alpha};T_i^{\beta};T_i^{\gamma}). \tag{30}$$

$$\tilde{S}_{i} = \bigoplus_{j=1}^{m^S}\tilde{w}_j^{S}\otimes\tilde{S}_{ij} = (S_i^{\alpha};S_i^{\beta};S_i^{\gamma}); \tag{31}$$

$$\tilde{W}_{i} = \bigoplus_{j=1}^{m^W}\tilde{w}_j^{W}\otimes\tilde{W}_{ij} = (W_i^{\alpha};W_i^{\beta};W_i^{\gamma}). \tag{32}$$

Stage 11. All strategic alternatives are positioned on the matrices according to the criteria *O* – *T* and *S* – *W* (Fig. 7). To consider different levels of uncertainty ("refinement of the obtained fuzzy estimates”), it is possible to use the α-section of a fuzzy number [33]. Note that if a given fuzzy number $\tilde{u}=(a,b,c)$, its α-section is determined as follows $\tilde{u}_{\alpha}=(a(1-\alpha)+\alpha b,\ b,\ c(1-\alpha)+\alpha b))$.

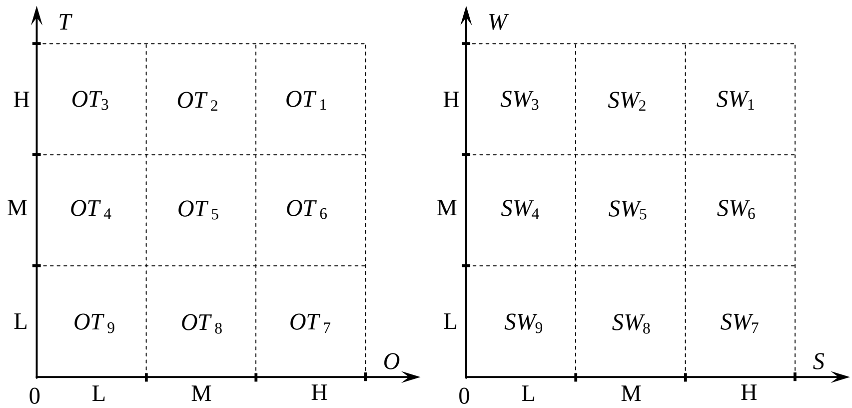

Fig. 7. Fuzzy matrixes for the evaluation of strategic alternatives

Fig. 8 shows an example of the construction of fuzzy evaluation matrices [6] of strategic alternatives according to the generalized criteria *O* – *T* and *S* – *W*.

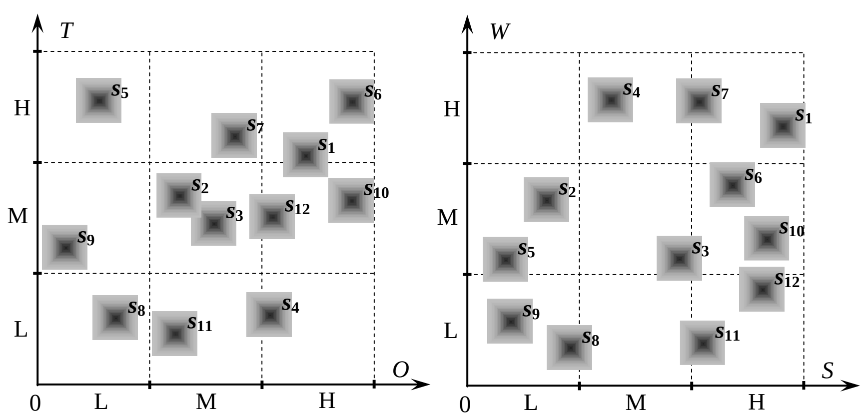

Fig. 8. An example of constructing fuzzy matrices for evaluating strategic alternatives according to the *O* – *T* and *S* – *W* criteria

Stage 12. The superposition of fuzzy matrices (*O* – *T*) and (*S* – *W*) is carried out by "superimposing" one matrix on another and considering possible combinations of "placements" of strategic recommendations in them. Further, experts should be involved in forming production rules for stratifying strategic alternatives, who should develop the conditions for belonging strategic alternatives to a particular stratum (Str_1, Str_2, ..., Str_p). An example of expert construction of such production rules is given below:

$$
\begin{aligned}
& if\ s_i \in OT_1\ and\ s_i \in SW_1 \\
& then\ s_i \in Str_1; \\
& if\ (s_i \in OT_1\ and\ s_i \in SW_2)\ or\ (s_i \in OT_2\ and\ s_i \in SW_1)\ or \\
& \quad (s_i \in OT_1\ and\ s_i \in SW_6)\ or\ (s_i \in OT_6\ and\ s_i \in SW_1) \\
& then\ s_i \in Str_2; \\
& if\ (s_i \in OT_2\ and\ s_i \in SW_6)\ or\ (s_i \in OT_6\ and\ s_i \in SW_2)\ or \\
& \quad (s_i \in OT_2\ and\ s_i \in SW_5)\ or\ (s_i \in OT_5\ and\ s_i \in SW_2)\ or \\
& \quad (s_i \in OT_1\ and\ s_i \in SW_5)\ or\ (s_i \in OT_5\ and\ s_i \in SW_1) \\
& then\ s_i \in Str_3; \\
& if\ (s_i \in OT_1\ and\ s_i \in SW_3)\ or\ (s_i \in OT_3\ and\ s_i \in SW_1)\ or \\
& \quad (s_i \in OT_1\ and\ s_i \in SW_7)\ or\ (s_i \in OT_7\ and\ s_i \in SW_1) \\
& then\ s_i \in Str_4; \\
& if\ (s_i \in OT_1\ and\ s_i \in SW_4)\ or\ (s_i \in OT_4\ and\ s_i \in SW_1)\ or \\
& \quad (s_i \in OT_1\ and\ s_i \in SW_8)\ or\ (s_i \in OT_8\ and\ s_i \in SW_1)\ or \\
& \quad (s_i \in OT_2\ and\ s_i \in SW_3)\ or\ (s_i \in OT_3\ and\ s_i \in SW_2)\ or \\
& \quad (s_i \in OT_6\ and\ s_i \in SW_7)\ or\ (s_i \in OT_7\ and\ s_i \in SW_6)\ or \\
& \qquad\qquad (s_i \in OT_5\ and\ s_i \in SW_5) \\
& then\ s_i \in Str_5; \\
& if\ (s_i \in OT_2\ and\ s_i \in SW_4)\ or\ (s_i \in OT_4\ and\ s_i \in SW_2)\ or \\
& \quad (s_i \in OT_6\ and\ s_i \in SW_8)\ or\ (s_i \in OT_8\ and\ s_i \in SW_6)\ or
\end{aligned}
$$

$$(s_i \in OT_5 \ \ and \ \ s_i \in SW_3)\ or\ (s_i \in OT_3 \ \ and \ \ s_i \in SW_5)\ or$$
$$(s_i \in OT_5 \ \ and \ \ s_i \in SW_7)\ or\ (s_i \in OT_7 \ \ and \ \ s_i \in SW_5)\ or$$
$$(s_i \in OT_1 \ \ and \ \ s_i \in SW_9)\ or\ (s_i \in OT_9 \ \ and \ \ s_i \in SW_1)$$
$$then \ \ s_i \in Str_6;$$
$$if\ (s_i \in OT_5 \ and \ s_i \in SW_4)\ or\ (s_i \in OT_4 \ and \ s_i \in SW_5)\ or$$
$$(s_i \in OT_5 \ \ and \ \ s_i \in SW_8)\ or\ (s_i \in OT_8 \ \ and \ \ s_i \in SW_5)\ or$$
$$(s_i \in OT_2 \ \ and \ \ s_i \in SW_9)\ or\ (s_i \in OT_9 \ \ and \ \ s_i \in SW_2)\ or$$
$$(s_i \in OT_6 \ \ and \ \ s_i \in SW_9)\ or\ (s_i \in OT_9 \ \ and \ \ s_i \in SW_6)$$
$$then \ \ s_i \in Str_7;$$
$$if\ (s_i \in OT_3 \ and \ s_i \in SW_4)\ or\ (s_i \in OT_4 \ and \ s_i \in SW_3)\ or$$
$$(s_i \in OT_7 \ \ and \ \ s_i \in SW_8)\ or\ (s_i \in OT_8 \ \ and \ \ s_i \in SW_7)\ or$$
$$(s_i \in OT_5 \ \ and \ \ s_i \in SW_9)\ or\ (s_i \in OT_9 \ \ and \ \ s_i \in SW_5)$$
$$then \ \ s_i \in Str_8;$$
$$if\ (s_i \in OT_3 \ and \ s_i \in SW_9)\ or\ (s_i \in OT_9 \ and \ s_i \in SW_3)\ or$$
$$(s_i \in OT_7 \ \ and \ \ s_i \in SW_9)\ or\ (s_i \in OT_9 \ \ and \ \ s_i \in SW_7)\ or$$
$$(s_i \in OT_4 \ \ and \ \ s_i \in SW_8)\ or\ (s_i \in OT_8 \ \ and \ \ s_i \in SW_4)$$
$$then \ \ s_i \in Str_9;$$
$$if\ (s_i \in OT_4 \ and \ s_i \in SW_9)\ or\ (s_i \in OT_9 \ and \ s_i \in SW_4)\ or$$
$$(s_i \in OT_8 \ \ and \ \ s_i \in SW_9)\ or\ (s_i \in OT_9 \ \ and \ \ s_i \in SW_8)$$
$$then \ \ s_i \in Str_{10};$$
$$if\ s_i \in OT_9 \ \ and \ \ s_i \in SW_9$$
$$then \ \ s_i \in Str_{11}.$$

Regarding the implementation of this stage, next comments should be considered:

1) when constructing production rules, the importance of each direction can be taken into account, which can be determined, for example, using the fuzzy SMART method, Fuzzy AHP or Fuzzy SBWM;

2) the given production rules can be written using the obtained membership functions of fuzzy estimates of strategic alternatives, and the stratification process can be easily automated;

3) the number of strata can be determined depending on the task (select the best strategic alternative, the most important and other alternatives, etc.).

Stage 13. Stratification of alternatives is carried out based on the application of developed production rules. In particular, for the case shown in Fig. 8, applying the above production rules, we get 8 strata: $Str_1 : \{ s_1 \}$; $Str_2 : \{ s_6, s_7 \}$; $Str_3 : \{ s_{10} \}$; $Str_4 : \{ s_3, s_4, s_{12} \}$; $Str_5 :$ $\{ s_2 \}$; $Str_6 : \{ s_5, s_{11} \}$; $Str_7 : \{ s_9 \}$; $Str_8 : \{ s_8 \}$.

Note that the Fuzzy SAW method can be used for stratification (and ranking) of strategic alternatives based on the obtained fuzzy integral values $\tilde{O}_i$, $\tilde{T}_i$, $\tilde{S}_i$ and $\tilde{W}_i$ if the weighting coefficients of the generalized "criteria" are determined. Indeed, if $\tilde{w}^O$, $\tilde{w}^T$, $\tilde{w}^S$ and $\tilde{w}^W$ are their respective fuzzy weighting coefficients, then the fuzzy evaluation of the "priority" of the i-th ($i = \overline{1, n}$) strategic alternative is based on the formula:

$$\tilde{P}(s_i) = \tilde{w}^O \otimes \tilde{O}_i \oplus \tilde{w}^T \otimes \tilde{T}_i \oplus \tilde{w}^S \otimes \tilde{S}_i \oplus \tilde{w}^W \otimes \tilde{W}_i . \quad (33)$$

This approach can be used to verify the results obtained by the basic model or, if necessary, to rank strategic alternatives.

At stage 14, a strategy is selected for implementation at the enterprise, or a group of preferable alternatives is selected for consideration by top management.

Let us make a few remarks about the validity of the proposed model, which is ensured by the use of verification procedures:

1) reaching a consensus by the expert group regarding the selection of the best and worst factors for each direction of analysis;

2) consistency of individual opinions of experts;

3) consistency of group assessments of experts in the best and worst approaches for each direction of analysis;

4) coherence of experts when evaluating strategic alternatives for each direction of analysis.

The framework has been developed in the Excel software application to implement the methodical approach, which contains the following main blocks (Fig. 9) and provides the possibility of simulation modelling depending on the input estimates of experts.

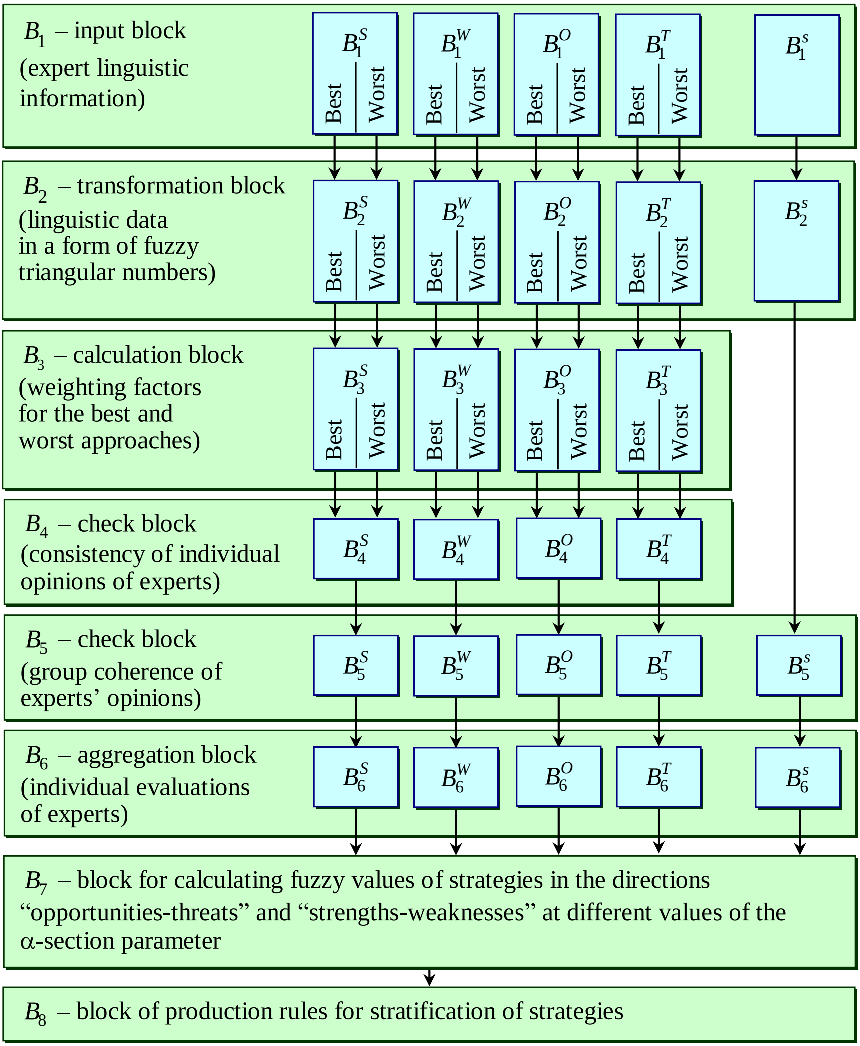

Fig. 9. Basic blocks of the framework for stratification of strategic alternatives of the enterprise

Conclusions and discussion

The need to improve existing and develop new methodological approaches to strategic choice in the strategic planning of an enterprise is due to the ever-increasing turbulence, complexity, instability, uncertainty and ambiguity of the environment for its functioning since an unsuccessful choice of a strategic direction is costly for the company and, in the worst case, can lead to its bankruptcy. Problematic aspects of this process are the formation of a system of criteria for evaluating strategic alternatives, the fuzziness of expert assessments and, accordingly, the need to use fuzzy multi-criteria analysis tools to select strategies for implementation. This study uses the criteria of the classical quantitative matrix of strategic planning (SWOT-factors), to determine the weighting factors of which the Fuzzy Extension of the Simplified Best-Worst Method is applied. Model is based on expert linguistic assessments for certain term sets (8-level – to determine the importance of SWOT factors and 7-level – to evaluate strategic alternatives) with their subsequent transformation into fuzzy numbers with triangular membership functions.

The second problem is proposed to be solved with the help of the Fuzzy SAW method (to determine fuzzy integral estimates of strategic alternatives in these areas) and fuzzy matrices “O – T” and “S – W”, in which developed strategic alternatives are positioned. Stratification of strategies for strategic choice is carried out based on the superposition of fuzzy matrices and the application of production rules of Mamdani fuzzy inference system developed by experts for the obtained integral fuzzy estimates of strategic alternatives.

In order to facilitate calculations according to this approach, a framework has been developed in the Excel software application, which can be the basis for creating appropriate support systems for making strategic management decisions to identify the list of preferable strategic alternatives.

Further research on the topic of the article can be aimed at improving individual stages of this methodological approach, in particular at:

– formation of a list of criteria for evaluating strategic alternatives, taking into account their focus on achieving strategic goals;

– complex application of several calculation schemes for assessing weighting factors of evaluation criteria based on fuzzy methods of multi-criteria analysis (Fuzzy AHP, Fuzzy SMART);

– optimization of parameters of the Mamdani fuzzy inference system on real data;

– development of a strategic decision-making support system based on the proposed framework using Fuzzy Logic Toolbox, Fuzzy Control Design Toolbox, fuzzyTECH, etc.

References

1. Abraham, S. (2012). *Strategic Planning: A Practical Guide for Competitive Success* (2nd ed.). Emerald Publishing.

2. Acur, N., & Englyst, L. (2006). Assessment of strategy formulation: how to ensure quality in process and outcome. *International Journal of Operations & Production Management*, *26*(1), 69-91. https://doi.org/10.1108/01443570610637021

3. Amiri, M., Tabatabaei, M.H., Ghahremanloo, M., Keshavarz-Ghorabaee, M., Zavadskas, E.K., & Antucheviciene, J. (2020). A new fuzzy approach based on BWM and fuzzy preference programming for hospital performance evaluation: A case study. *Applied Soft Computing*, *92*, Article 106279. https://doi.org/10.1016/j.asoc.2020.106279

4. Ansoff, I. (1979). *Strategic Management*. Palgrave Macmillan. https://doi.org/10.1007/978-1-349-02971-6

5. Balan, V. (2020). Nechitka model otsiniuvannia ta vyboru stratehii na osnovi modyfikatsii kvantytatyvnoi matrytsi stratehichnoho planuvannia [Fuzzy model of evaluation and selection of strategies based on modification of the quantitative strategic planning matrix]. *Problemy systemnoho pidkhodu v ekonomitsi (Problems of systemic approach in the economy)*, *3*(77), 85-93. https://doi.org/10.32782/2520-2200/2020-3-12 [in Ukrainian]

6. Balan, V. (2020). Zastosuvannia dynamichnoho nechitkoho SPACE-analizu dlia formuvannia stratehii pidpryiemstva [Application of dynamic fuzzy SPACE-analysis for forming enterprise strategies]. *Neiro-Nechitki Tekhnolohii Modelyuvannya v Ekonomitsi (Neuro-Fuzzy Modeling Techniques in Economics)*, *9*, 26-64. http://doi.org/10.33111/nfmte.2020.026 [in Ukrainian]

7. Chang, P., Huang, L., & Lin, H. (2000). The fuzzy Delphi method via fuzzy statistics and membership function fitting and an application to the human resources. *Fuzzy Sets and Systems*, *112*(3), 511-520. https://doi.org/10.1016/S0165-0114(98)00067-0

8. David, F.R. (2015). *Strategic management: concepts and cases – a competitive advantage approach*. Pearson Education.

9. David, M.E., David, Fred R., & David, Forest R. (2016). The quantitative strategic planning matrix: a new marketing tool. *Journal of Strategic Marketing*, *25*(4), 342-352. http://dx.doi.org/10.1080/0965254X.2016.1148763

10. Day, G.S. (1994). *Evaluating Strategic Alternatives*. In L. Fahey, & M.R. Randall (Eds.), *The Portable MBA in Strategy* (pp. 297-317). John Wiley & Sons, Inc.

11. Dong, J., Wan, S., & Chen, S.-M. (2021). Fuzzy best-worst method based on triangular fuzzy numbers for multi-criteria decision-making. *Information Sciences*, *547*, 1080-1104. https://doi.org/10.1016/j.ins.2020.09.014

12. Fahey, L., & Randall, R.M. (2001). *The Portable MBA in Strategy*. John Wiley & Sons, Inc.

13. Fleisher, K., & Bensoussan, B. (2002). *Strategic and Competitive Analysis: Methods and Techniques for Analyzing Business Competition*. Pearson College Div.

14. Fouladgar, M., Yazdani-Chamzini, A., & Yakhchali, S. (2011). A new methodology for prioritizing mining strategies. *International Journal of Innovation, Management and Technology*, *2*(4), 342-347. http://www.ijimt.org/show-32-603-1.html

15. Friedrichsen, M., Zarea, H., Tayebi, A., & Abad, F.A.S. (2018). Competitive strategies of knowledge and innovation commercialization: a unified SWOT and Fuzzy AHP approach. *AD-minister*, *30*, 45-72. https://doi.org/10.17230/ad-minister.30.3

16. Gaonkar, R.S.P., Verma, A.K., & Srividya, A. (2008). Exploring Fuzzy Set Concept in Priority Theory for Maintenance Strategy Selection Problem. *The International Journal of Applied Management and Technology*, *6*(3), 131-142. https://core.ac.uk/works/125807675

17. Glueck, W.F., & Jauch, L.R. (1984). *Strategic Management and Business Policy*. McGraw-Hill.

18. Grant, R.M. (2021). *Contemporary Strategy Analysis* (11th ed.). Wiley.

19. Guo, S., & Qi, Z. (2021). A Fuzzy Best-Worst Multi-Criteria Group Decision-Making Method. *IEEE Access*, *9*, 118941–118952. https://doi.org/10.1109/ACCESS.2021.3106296

20. Guo, S., & Zhao, H. (2017). Fuzzy best-worst multi-criteria decision-making method and its applications. *Knowledge-Based Systems*, *121*, 23-31. https://doi.org/10.1016/j.knosys.2017.01.010

21. Hafezalkotob, A., & Hafezalkotob, A. (2017). A novel approach for combination of individual and group decisions based on fuzzy best-worst method. *Applied Soft Computing*, *59*, 316-325. https://doi.org/10.1016/j.asoc.2017.05.036

22. Hamal, S., Sennaroglu, B., & Arıoğlu, M.Ö. (2020). Marketing Strategy Selection Using Fuzzy Analytic Network Process. In C. Kahraman, S. Cevik Onar, B. Oztaysi, I. Sari, S. Cebi, & A. Tolga (Eds.), *Advances in Intelligent Systems and Computing: Vol. 1197. Intelligent and Fuzzy Techniques: Smart and Innovative Solutions* (pp. 1008-1014). Springer. https://doi.org/10.1007/978-3-030-51156-2_117

23. Hussey, D.E. (1998). *Strategic Management. From theory to implementation*. Butterworth-Heinemann.

24. Hussey, D.E. (1999). *Strategy and Planning: A Manager's Guide.* Wiley.

25. Jeyaraj, K.L., Muralidharan, C., Senthilvelan, T., & Deshmukh, S.G. (2012). A hybrid business strategy selection process for a Textile company using SWOT and fuzzy ANP – a case study. *International Journal of Management*, *3*(2), 124-143. https://iaeme.com/Home/article_id/IJM_03_02_012

26. Johnson, G., Scholes, K., & Whittington, R. (2008). *Exploring corporate strategy* (8th ed.). Financial Times Prentice Hall.

27. Kokoç, M., Ersöz, S., & Aktepe, A. (2020) A Fuzzy Inference System Proposal for Selecting Marketing Strategy. *International Journal of Eastern Anatolia Science Engineering and Design*, *2*(1), 1-21. https://dergipark.org.tr/en/pub/ijeased/issue/50819/653763

28. Kotler, Ph., Berger, R. & Bickhoff, N. (2016). *The Quintessence of Strategic Management: What You Really Need to Know to Survive in Business*. Springer.

29. Kozlovskyi, S., Butyrskyi, A., Poliakov, B., Bobkova, A., Lavrov, R., & Ivanyuta, N. (2019). Management and comprehensive assessment of the probability of bankruptcy of Ukrainian enterprises based on the methods of fuzzy sets theory. *Problems and Perspectives in Management*, *17*(3), 370–381. http://dx.doi.org/10.21511/ppm.17(3).2019.30

30. Kuzu, Ö.H. (2020). Strategy Selection in the Universities via Fuzzy AHP Method: A Case Study. *International Journal of Higher Education*, *9*(2), 107-117. https://doi.org/10.5430/ijhe.v9n2p107

31. Laczkowski, K., Rehm, W., & Warner, B. (2018). *Seeing your way to better strategy*. McKinsey & Company. https://www.mckinsey.com/capabilities/strategy-and-corporate-finance/our-insights/seeing-your-way-to-better-strategy#/

32. Lampel, J., Mintzberg, H., Quinn, J.B., & Ghoshal, S. (2014). *The Strategy Process: Concepts, Contexts, Cases* (5th ed.). Trans-Atlantic Publications.

33. Leekwijck, W., & Kerre, E.E. (1999). Defuzzification: criteria and classification. *Fuzzy Sets and Systems*, *108*(2), 159-178. https://doi.org/10.1016/S0165-0114(97)00337-0

34. Leleur, S. (2012). *Complex Strategic Choices. Applying Systemic Planning for Strategic Decision Making*. Springer London. https://doi.org/10.1007/978-1-4471-2491-7

35. Matviychuk, A. (2010). Bankruptcy prediction in transformational economy: discriminant and fuzzy logic approaches. *Fuzzy economic review*, *15*(1), 21–38. https://doi.org/10.25102/fer.2010.01.02

36. Mohaghar, A., Fathi, M.R., Zarchi, M.K., & Omidian, A. (2012). A Combined VIKOR - Fuzzy AHP Approach to Marketing Strategy Selection. *Business Management and Strategy*, *3*(1), 13-27. https://doi.org/10.5296/bms.v3i1.957

37. Mohammadi, A., Mohammadi, Ab., Zarifpayam, S.V., & Mohammadi, M. (2011). Presentation of Fuzzy Models of EFE, IFE and QSPM. *Australian Journal of Basic and Applied Sciences*, *5*(12), 1173-1179. https://www.ajbasweb.com/old/ajbas/2011/December-2011/1173-1179.pdf

38. Nasab, H.H., & Milani, A.S. (2012). An improvement of quantitative strategic planning matrix using multiple criteria decision making and fuzzy numbers. *Applied Soft Computing*, *12*(8), 2246-2253. https://doi.org/10.1016/j.asoc.2012.03.010

39. Rezaei, J. (2015). Best-worst multi-criteria decision-making method. *Omega*, *53*, 49-57. https://doi.org/10.1016/j.omega.2014.11.009

40. Rezaei, J. (2016). Best-worst multi-criteria decision-making method: Some properties and a linear model. *Omega*, *64*, 126-130. https://doi.org/10.1016/j.omega.2015.12.001

41. Rumelt, R. (1980). The Evaluation of Business Strategy. In W. F. Glueck (Ed.), *Business Policy and Strategic Management* (3rd ed., pp. 359-367). McGraw-Hill.

42. Sagar, M. K., Jayaswal, P., & Kushwah, K. (2013). Exploring Fuzzy SAW Method for Maintenance Strategy Selection Problem of Material Handling Equipment. *International Journal of Current Engineering and Technology*, *3*(2), 600-605. https://inpressco.com/exploring-fuzzy-saw-method-for-maintenance-strategy-selection-problem-of-material-handling-equipment/

43. Thompson, A.A., & Strickland, A.J. (2003). *Strategic Management: Concepts and Cases* (13th ed.). McGraw Hill.

44. Wheelen, T.L., Hunger, J.D., Hoffman, A.N., & Bamford, C.E. (2018). *Strategic Management and Business Policy. Globalization, Innovation, and Sustainability* (15th ed.). Pearson Education Limited.

45. Zadeh, L.A. (1978). Fuzzy Sets as a Basis for a Theory of Possibility. *Fuzzy Sets and Systems*, *1*(1), 3-28. https://doi.org/10.1016/0165-0114(78)90029-5

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4.2. Kobets, V., Yatsenko, V., & Voynarenko, M. (2020). Cluster Analysis of Countries Inequality Due to IT Development Through Macros Application. In V. Ermolayev, F. Mallet, V. Yakovyna, H. Mayr, & A. Spivakovsky (Eds.), *Communications in Computer and Information Science: Vol. 1175. Information and Communication Technologies in Education, Research, and Industrial Applications* (pp. 415–439). Springer. https://doi.org/10.1007/978-3-030-39459-2_19

4.3. Wysocki, A., & Ławryńczuk, M. (2015). Jordan neural network for modelling and predictive control of dynamic systems. In *Proceedings of 2015 20th International Conference on Methods and Models in Automation and Robotics* (pp. 145-150). IEEE. https://doi.org/10.1109/MMAR.2015.7283862

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6.2. Claessens, S., & Kose, M.A. (2013). *Financial Crises: Explanations, Types, and Implications* (Working Paper 13/28). International Monetary Fund. https://www.imf.org/external/pubs/ft/wp/2013/wp1328.pdf

6.3. Eurostat. (2017, October 17). *EU trade in food*. https://ec.europa.eu/eurostat/web/products-eurostat-news/-/edn-20171016-1

7. Wikipedia.

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