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Assessing the Level of Employment in the Informal Sector of the Economy of Russian Regions Using Modern Machine Learning Methods

A.N. Borisov[a], A.I. Borodin[b], R.V. Gubarev[c], E.I. Dzyuba[d], O.M. Kulikova[e]
[a] MGIMO University, Moscow, Russia;
[b, c] Plekhanov Russian University of Economics, Moscow, Russia;
[d] Institute of social and Economic Research of the UFRC of the RAS, Ufa, Russia;
[e] Siberian State Automobile and Highway University, Omsk, Russia

ABSTRACT

The global trend is mass employment of the population in the informal sector of the economy. At the same time, only in economically developed countries of the world such workers have relatively good working conditions. At the current stage of development, Russia is among the group of actively economically developing countries of the world. Therefore, the improvement of the mechanism of state social protection of those employed in the informal sector of the economy remains an **urgent relevant issue** for our country, which, in turn, implies monitoring of the situation. **The purpose** of this study is to develop tools for such monitoring with the help of artificial intelligence (more precisely, modern machine learning **methods**). According to the results of cluster analysis carried out using the k-means **method** in the Python programming language, it was found that in modern Russia there is a high degree of differentiation of regions by the level of employment in the informal sector of the economy. At the same time, most of the subjects of the Russian Federation are characterised by the same situation as in economically developing countries of Eastern Europe (Bosnia and Herzegovina, Serbia, Czech Republic). Four regions of Russia (from the North Caucasus Federal District) have an abnormally high level of employment in the informal sector of the economy comparable only with economically developing countries of Asia, Africa, North and South America. In the course of solving the classification problem using a modern machine learning method (LightGBM), the key factors affecting the level of employment in the informal sector of the economy of Russian regions were identified. According to the classification results, we can **conclude** that a cardinal change in the current situation is not expected in the future. Therefore, for modern Russia, it is necessary to improve the state social policy for a significant part of the regions. **The results** of the empirical study can be applied to improve the effectiveness of the state social policy of the Russian Federation. Thus, in particular, it will be possible to specify the amount of financial resources required for additional social support of the employed population of certain regions of our country.

Keywords: regions of Russia; employment level; informal sector of the economy; precariat; machine learning; clustering; classification; forecasting

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ОРИГИНАЛЬНАЯ СТАТЬЯ

Оценка уровня занятости в неформальном секторе экономики регионов России с помощью современных методов машинного обучения

А.Н. Борисов[a], А.И. Бородин[b], Р.В. Губарев[c], Е.И. Дзюба[d], О.М. Куликова[e]
[a] МГИМО МИД России, Москва, Россия;
[b, c] Российский экономический университет имени Г.В. Плеханова, Москва, Россия;
[d] Институт социально-экономических исследований УФИЦ РАН, Уфа, Россия;
[e] Сибирский государственный автомобильно-дорожный университет, Омск, Россия

АННОТАЦИЯ

Общемировой тенденцией является массовая занятость населения в неформальном секторе экономики. При этом только в экономически развитых странах мира такие занятые имеют относительно хорошие условия труда. На современном этапе развития Россия входит в группу активно экономически развивающихся стран мира. Поэтому для нашей страны **актуальным** вопросом остается совершенствование механизма государственной социальной защиты занятых в неформальном секторе экономики, что, в свою очередь, предполагает мониторинг ситуации. **Целью** данного исследования является развитие инструментария для такого мониторинга с помощью искусственного интеллекта (точнее, современных **методов** машинного обучения). По итогам кластерного анализа, проведенного с помощью **метода** k-means на языке программирования Python, было установлено, что в современной России наблюдается высокая степень дифференциации регионов по уровню занятости в неформальном секторе экономики. При этом для большей части субъектов РФ характерна ситуация, что и в экономически развивающихся странах Восточной Европы (Боснии и Герцеговине, Сербии, Чехии). В четырех регионах России (из Северо-Кавказского федерального округа) наблюдается аномально высокий уровень занятости в неформальном секторе экономики, сопоставимый только с экономически развивающимися странами Азии, Африки, Северной и Южной Америки. В ходе решения задачи классификации с помощью современного **метода** машинного обучения (LightGBM) были выявлены ключевые факторы, влияющие на уровень занятости в неформальном секторе экономики регионов России. По итогам классификации можно сделать **вывод**, что кардинальное изменение сложившейся ситуации в перспективе не ожидается. Поэтому для современной России необходимо совершенствование государственной социальной политики в отношении значительной части регионов. **Результаты** эмпирического исследования могут быть применены для повышения эффективности государственной социальной политики РФ. Так, в частности можно будет уточнить объем финансовых ресурсов, необходимых на дополнительную социальную поддержку занятого населения определенных регионов нашей страны.

Ключевые слова: регионы России; уровень занятости; неформальный сектор экономики; прекариат; машинное обучение; кластеризация; классификация; прогнозирование

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Introduction

Currently, more than 2 billion people, or 60% of the world labor market, are covered by informal employment [1]. One worldwide trend is that a sizable portion of the working population in various nations is frequently classified as informally employed. The indicator is also marked by abnormally high readings in some countries. For example, in 2021, the level (in percent of the working-age population) of informally employed in Angola was 69.3%, in Vietnam — 68.3%, in Guatemala — 89.3%, Zambia — 73.5%, Zimbabwe — 75.7%, India — 71.3%, Comoros — 91.4%, Pakistan — 67.5%, Paraguay — 70.1%, Peru — 68%, Rwanda — 74.7%, El Salvador — 70.6% and Uganda — 97.8%. The most favorable situation on the level of informal employment was observed in a number of economically developed countries in Europe: in Austria the value of the indicator was 5.1%, Belgium — 2.9%, Germany — 2.8%, Ireland — 1.7%,

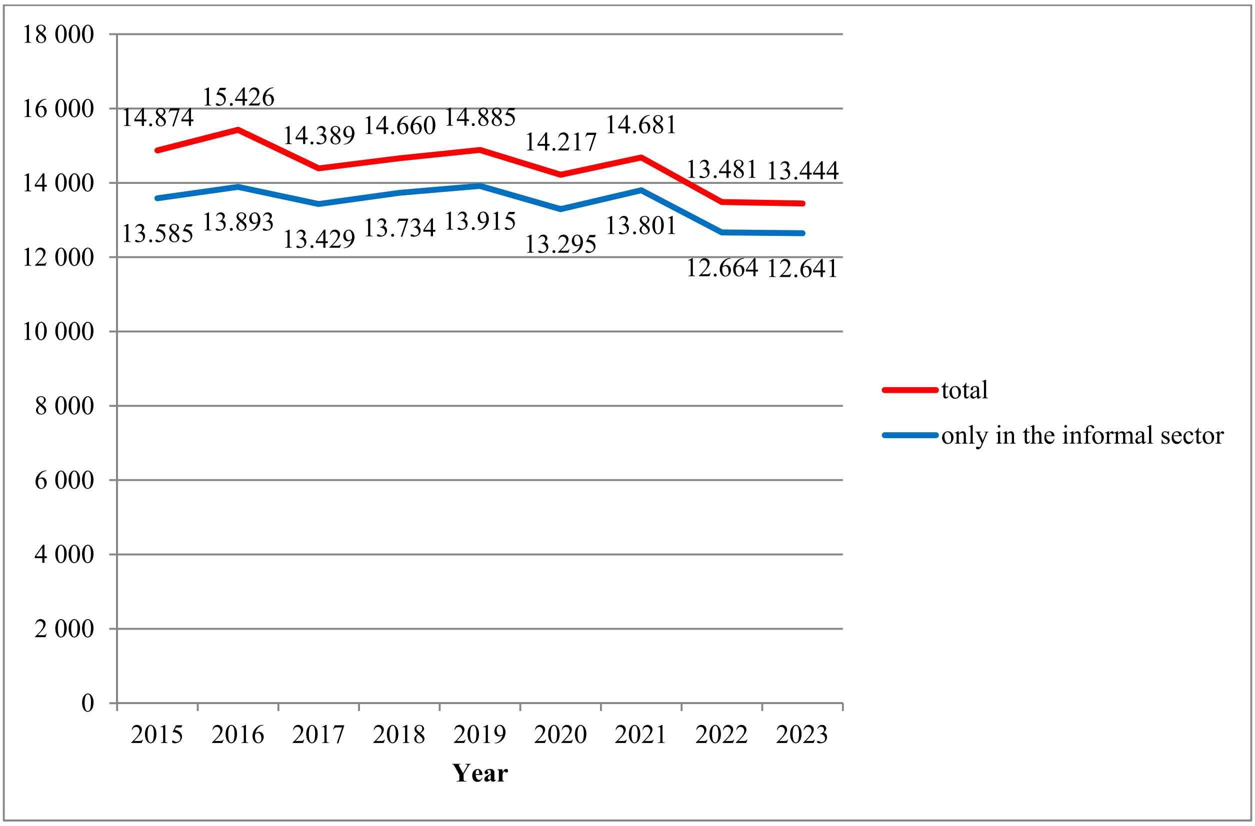

Fig. 1. **Change in the number of employees in the informal sector of the Russian economy (by the type of employment) for 2015–2023, thousand people**

Source: Compiled by the authors according to the data of the Labor Force, Employment and Unemployment in Russia (based on the results of sample labor force surveys). 2024 Stat.sb. Moscow: Rosstat; 2024.

Spain — 5.1%, Finland — 5%, France — 3.5% and Sweden — 2.6% in 2021 [2].

In Russia, this phenomenon is widespread as well as in a number of other countries of the world. It is known that most of the informally employed in modern Russia also work in the informal sector of the economy [3]. Therefore, within the framework of this study, we will limit ourselves to the study of employment in the informal sector of the national economy. Based on the data of official statistics, let us independently draw up a "portrait" of the employed in the informal sector of the economy of modern Russia. In *Fig. 1,* we visualize the change over the last 9 years for our country, both the total number of employed in the informal sector of the economy and their part with the only appropriate type of work.

As shown in *Fig. 1*, there was no definite trend of change in the values of the indicator for 2015–2023. However, over the entire analyzed period of time, the number of people employed in the informal sector of the Russian economy decreased from 14874 to 13444 thousand people (historical minimum), i.e., by almost 10%. At the same time, for about 90–91% in 2015–2016 and 93–94% throughout the rest of the period, such compatriots worked exclusively in the informal sector of the national economy.

Fig. 2 shows the change in the share of working Russians in the informal sector of the national economy by age groups.

According to *Fig. 2*, during the first 7 years of the analyzed period, the value of the indicator averaged about 20% in the country, except for 2016 (exceeded 21%). At present (as of 2023), the value of the share of those employed in the informal sector of the national economy has reached a historical minimum and is about 18%.

At the same time, the bulk of employed Russians in the informal sector of the economy is concentrated in two age groups: the youngest (from 15 to 19 years) and the oldest (70 years and older). Thus, the share of such workers was respectively about 42–49 and 36–39% of the total number of the employed of a certain age in different years of the analyzed period.

Fig. 3 visualizes the change in the structure of employed Russians in the informal sector by type of economic activity.

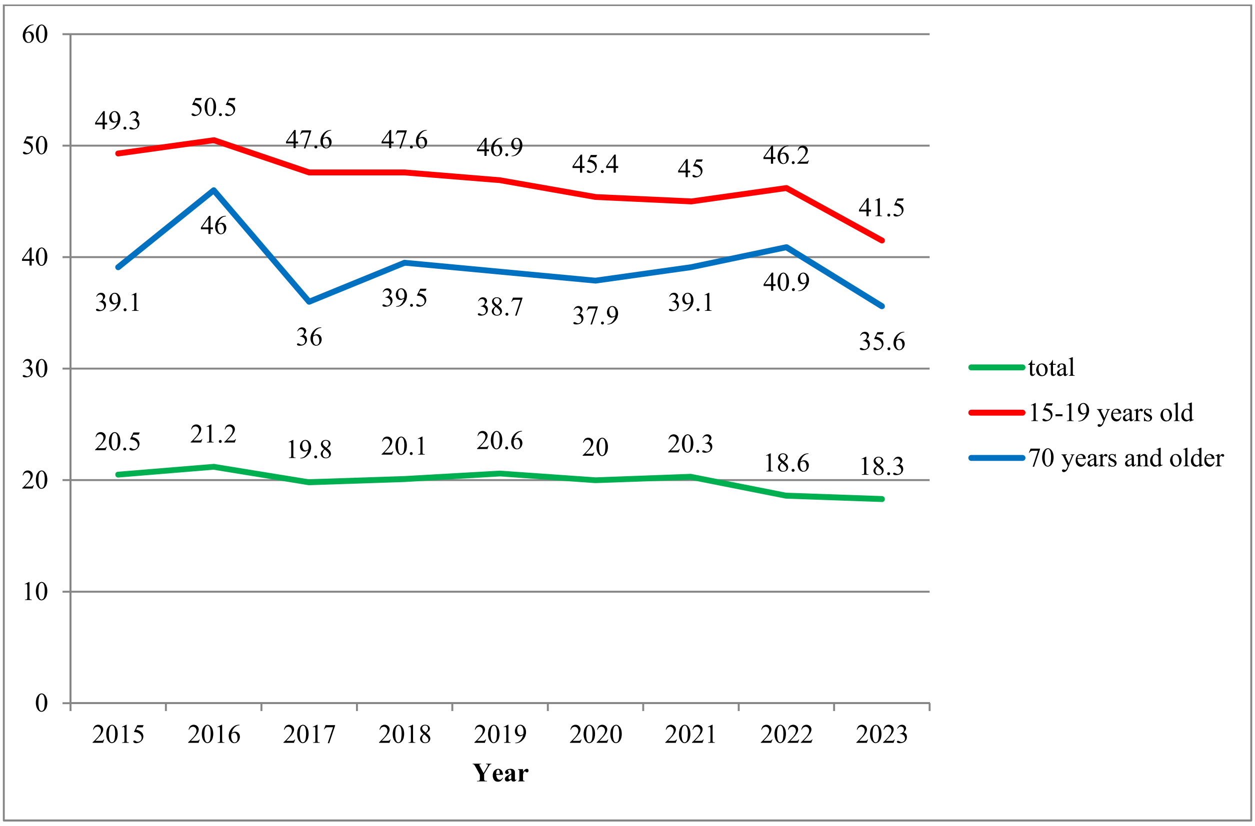

Fig. 2. **Change in the share of employees in the informal sector of the Russian economy (by age group) in 2015–2023,% (of total employment)**

Source: Compiled by the authors according to the data of the Labor Force, Employment and Unemployment in Russia (based on the results of sample labor force surveys). 2024 Stat.sb. Moscow: Rosstat; 2024.

As shown in *Fig. 3*, most of the employed Russians in the informal sector were distributed among five types of economic activity: agriculture, industry, construction, trade and transportation and warehousing logistics. The aggregate share of such workers was about 76–84% in different years of the analyzed period. At the same time, the most significant part of employed Russians in the informal sector of the economy (29–33%) in 2015–2023 worked in trade.

Summarizing the results of thematic analysis, we can conclude that informal employment for our country is a mass phenomenon. Thus, almost every 5th Russian works in the informal sector of the national economy. Moreover, for most of them, employment in the informal sector is the only place of work. At the same time, the composition of employed Russians in the informal sector of the economy, as a rule, includes young people and the elderly. Finally, their main place of work is in trade.

Literature review

In [4], it is rightly noted that the generally accepted approach to the study of the economy is to distinguish its two components (components): observed and unobserved. The second, in turn, includes underground, illegal, informal economies and the production of products by households for their own consumption. In this case, the informal sector of the national economy is understood as the legitimate market production of goods and services, but hidden from the state for monetary, regulatory or institutional reasons [5].

It should be noted that informal employment in economically developed and developing countries has fundamental differences. The main feature of informal employment for the first group of countries is relatively (compared to the second group of countries) good working conditions of the workers concerned [2, 6], which complicates the fight against such a phenomenon [7]. *Fig. 4* presents a number of important factors affecting the level of informal employment in different countries of the world. Along with the term "informal employment", scientists often use the closely related definitions "vulnerable employment" and "precarious employment". We adhere to the view that these terms have a close semantic meaning but are not synonyms.

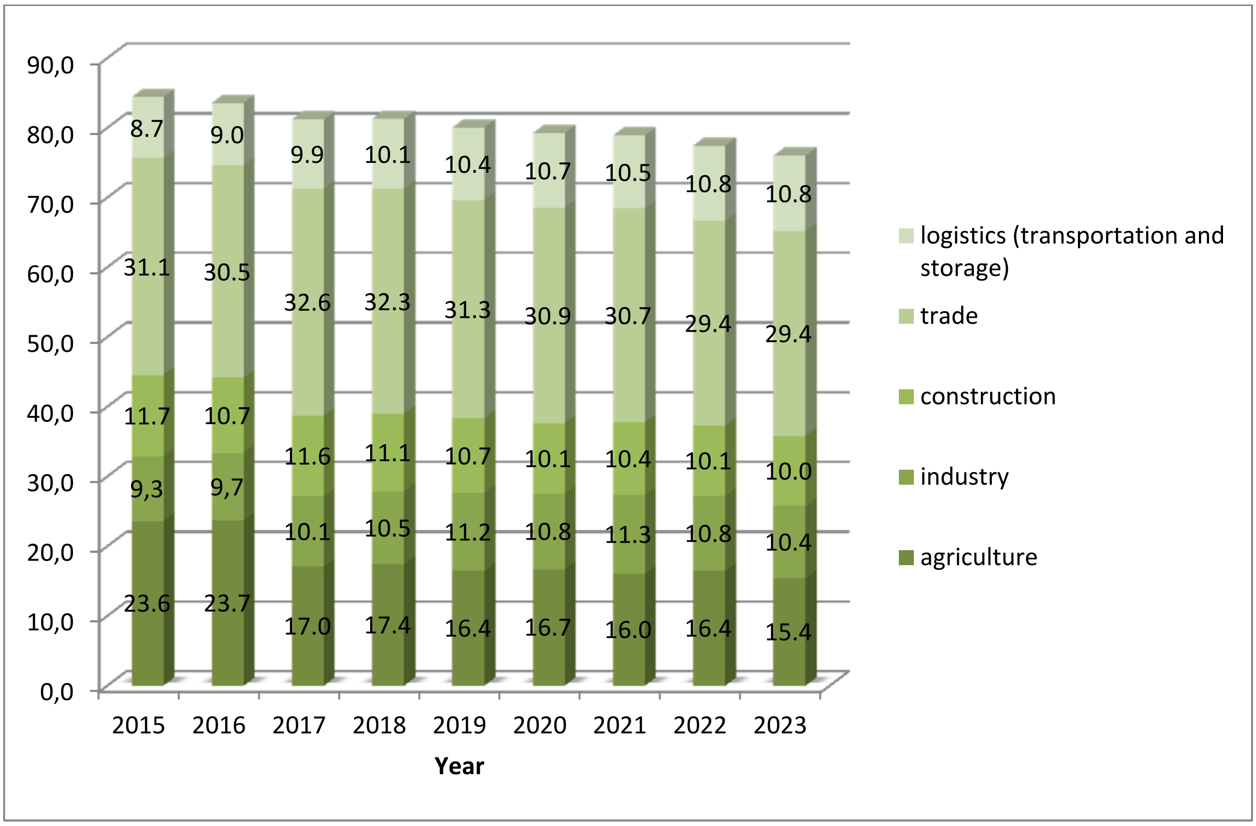

Fig. 3. **Change in the structure of employed Russians in the informal sector (by type of economic activity) for 2015–2023, %**

Source: Compiled by the authors according to the data of the Labor Force, Employment and Unemployment in Russia (based on the results of sample labor force surveys). 2024 Stat.sb. Moscow: Rosstat; 2024.

Sharing the opinion of the authors of [8], in the framework of this study we will consider informal employment as the main catalyst for the formation of precariat in our country.

In [18], it is rightly noted that, despite a significant number of thematic studies by foreign and Russian authors, the definition of "precarious employment" and the derivative term "precariat" still require clarification. Developing the thought, the scientist emphasizes the following: "…there is still no consensus even on the main issues related to it. There is no agreement neither on what criteria should be used to distinguish the precariat, nor on its social composition, nor even on its very existence as a class" [18, p. 105].

At the same time, most researchers have the main (sometimes the only) criterion for classifying the working population as precariat is the form of employment. Thus, for example, in [19], "workers who are employed under a temporary contract for less than a year or work without a labor contract at all" are referred to as the precariat. Another study by the previously mentioned author [20, p. 87] lists the main forms of informal employment: "temporary, casual, seasonal, secondary, part-time, as well as self-employment, platform employment and borrowed labor".

Also, there are works that present a multi-criteria procedure for categorizing a worker as precariat. For example, the article [21, p. 65] proposes a system of seven indicators or signs: "1) registration of labor without a contract or with a contract for no more than one year; 2) complete inconsistency of education with work; 3) overwork (more than 8 hours) permanent; 4) part-time work in their own or third-party organization (regular or irregular); 5) wages in an envelope (systematic or occasional); 6) change of job more than once in the last three years; 7) inability to influence important decisions in their work organization".

Corresponding member of the Russian Academy of Sciences J.T. Toshchenko [22] offers an almost identical system, including six main signs of precariat identification. Despite the existing discussion issues, most Russian researchers [19, 21, 23–28] adhere to the point of view about the

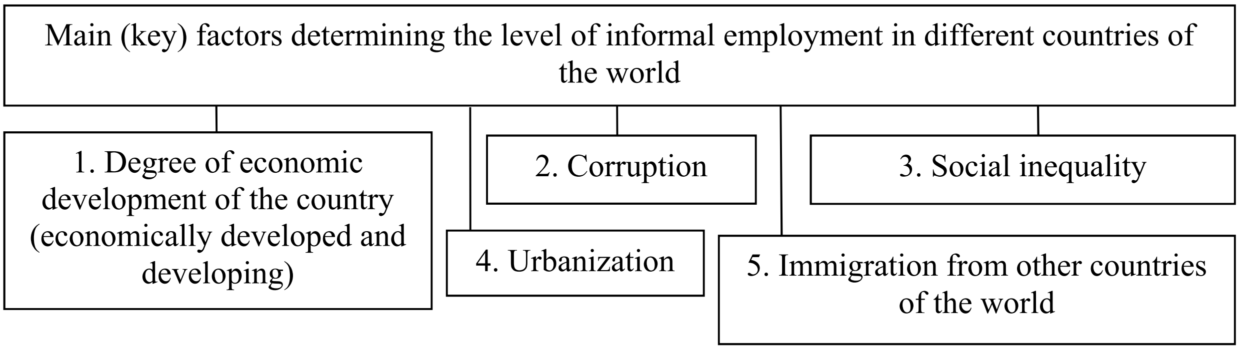

Fig. 4. **Key (main) factors affecting the level of informal employment in the world economy**

Source: Compiled by the authors on the basis of [2, 9–17].

negative impact of "precarious employment" on the quality of life of workers in the informal sector of the national economy. For example, in the work [28, p. 34] an important conclusion is made: "the public and private life of precarious workers vividly reveals social stratification in all the main characteristics of human life — in terms of labor employment guarantees, labor remuneration, the use of their intellectual and professional potential, and the sustainability of their daily life". Developing the idea [28, p. 34–35] focuses on the fact that "a constant feature of the life world of precarians is an isolationist position, manifested in anomie and loss of orientation, both in their future and the future of the country. The uncertainty of social and professional status, instability of well-being due to the lack of acceptable rules of labor remuneration, instability in the observance of social guarantees are complemented by the lack of a clearly articulated image of the future, which leads to the formation of indifference to political, economic and social life at all levels of social structure". It should be noted that the work of the Russian scientist largely agrees with the earlier results of a well-known foreign researcher [29, 30], who emphasized the infringement of various (civil, cultural and political) rights of the precariat.

Given the above, it is difficult to overestimate the importance of correct measurement of the quality of employment for modern Russia. In [31, p. 262] five most famous alternative approaches to measuring the quality of employment proposed by various international organizations are highlighted: "1) the global system of indicators for the UN Sustainable Development Goals; 2) Decent Work Indicators of the International Labor Organization; 3) guidelines for measuring the quality of the working environment of the Organization for Economic Cooperation and Development; 4) UN Economic Commission for Europe's initiative on measuring the quality of employment; 5) the quality of workplaces of the European Foundation for the Improvement of Living and Working Conditions together with the International Labor Organization".

The principal difference between the above approaches is the number of indicators used to assess the quality of employment. According to this criterion, all the variety of thematic methodologies developed by the scientific and expert community can also be grouped into three groups [31]: with one key (main) indicator, several private indicators and, finally, an integral (generalizing, summary) characteristic, which is the result of index construction ("convolution" of the values of a number of indicators according to a certain rule).

We believe that it is necessary to search for the optimal number of private indicators. An excessive number of indicators leads to "dilution" of results when decomposing the index. In addition, the labor intensity of thematic evaluation increases. In the reverse situation (minimum set of private indicators), the final result may be significantly distorted due to the fact that a number of significant factors are not taken into account.

Another equally important classification feature is the sources of information. Here, we can also distinguish three groups of thematic methodologies, which are based solely on statistical information or data from sociological surveys, and a mixed (hybrid) variant, when both of the above-mentioned sources of information are used simultaneously. Sample surveys (thematic surveys of the population) complement aggregated data of official statistics (formed on the basis of organizations' reports), but at the same time increase the subjectivity of the obtained estimates of employment quality.

Within the framework of this study, we will limit ourselves to measuring the quality of employment in our country with regard to the meso-level of management on the basis of one (main) indicator — the level of employment in the informal sector of the economy. Despite a significant number of case studies, there is virtually no research using genetic algorithm, artificial neural networks or modern machine learning techniques. One of the few such works is the article [32], where a not unsuccessful attempt to group Russian regions (their classification) depending on the level (calculated as a percent of the number of employed) of workers in the informal sector of Russian regions, more precisely, the key factors determining it using the random forest method (one of the methods of machine learning) was made.

Taking into account the above-mentioned, this study aims to develop an adequate modern toolkit for the realization of the predictive function in relation to the phenomenon under study. The hypothesis is put forward about the possibility of correct clustering and subsequent classification of RF subjects by the level of employment in the informal sector of the economy using a modern machine learning method.

Data and research methods

In the previously mentioned statistical compilation, the data on the number of employed in the informal sector of the national economy for the regions of Russia are given with a periodicity of once every two years. Therefore, the information base of this empirical study is the values of the studied indicators for 2017, 2019, 2021 and 2023. At the same time, the presence of lagged factor indicators in the initial system (with an offset of one year back in relation to the dependent variable) is explained by the "lagging" statistics in terms of the disclosure of data on gross regional product (GRP) by the subjects of the Russian Federation.

The dependent ("output") variable (result indicator) is the level of employment in the informal sector of the economy (expressed as a percentage of the total working population) in the Russian regions. Taking into account case studies by different authors [31–36], a system of twenty-five factor indicators ("input" or independent variables), including lag variables, was initially formed (*Fig. 5*). In *Fig. 5*, the 18th-21st indicators are lag-independent variables (with values shifted back one year) in relation to the 1st, 5th, 12th and 17th factors.

The decision on the expediency of including certain lag factor indicators was made taking into account the assessment of the strength of the influence of independent variables on the resultant indicator. Such strength was determined by calculating and analyzing pairwise Pearson's correlation coefficients (*Table 1*).

In order to ensure the comparability of the initial information in the spatial and temporal contexts, the cost indicators were preliminary adjusted. First, the influence of the price factor in dynamics was leveled out. Secondly, auxiliary calculations were made taking into account the purchasing power parity in the Russian regions. In this case, the cost of a fixed set of consumer goods and services in Moscow in 2017 was taken as a base of comparison (benchmark).

Table 1 does not show the factors that have a weak effect on the performance indicator (Pearson's pair correlation coefficient took values less than 0.4).

The strongest influence on the dependent variable (the value of the above coefficient was approximately 0.6–0.7), excluding lag factors (Z18–Z21), was exerted by a group of 6 "input" variables (Z1, Z5, Z9, Z10, Z12 and Z17). The final decision on the composition of factor indicators ("input" variables) for solving the classification problem is made during computational experiments. This task is solved within the framework of the study using one of the methods of modern machine learning — the LightGBM (Light Gradient-Boosting Machine) method. At the same time, it should be noted that the initial information for the classification of Russian regions in our case are the results of cluster analysis, i.e., the distribution of subjects of the Russian Federation into groups based on the level of employment in the informal sector of the economy. In turn, the clustering problem is solved using the k-means method in the Python programming language. Previously, the optimal number of clusters is determined using the Elbow method (*Fig. 6*).

As can be seen from the data in *Fig. 6*, based on the actual level of employment in the informal sector of the economy, it is reasonable to divide 82 Russian regions for 2017, 2019, 2021 and 2023 into five clusters. During a series of computational experiments, all observations were correctly recognized, i.e. the Russian regions were distributed

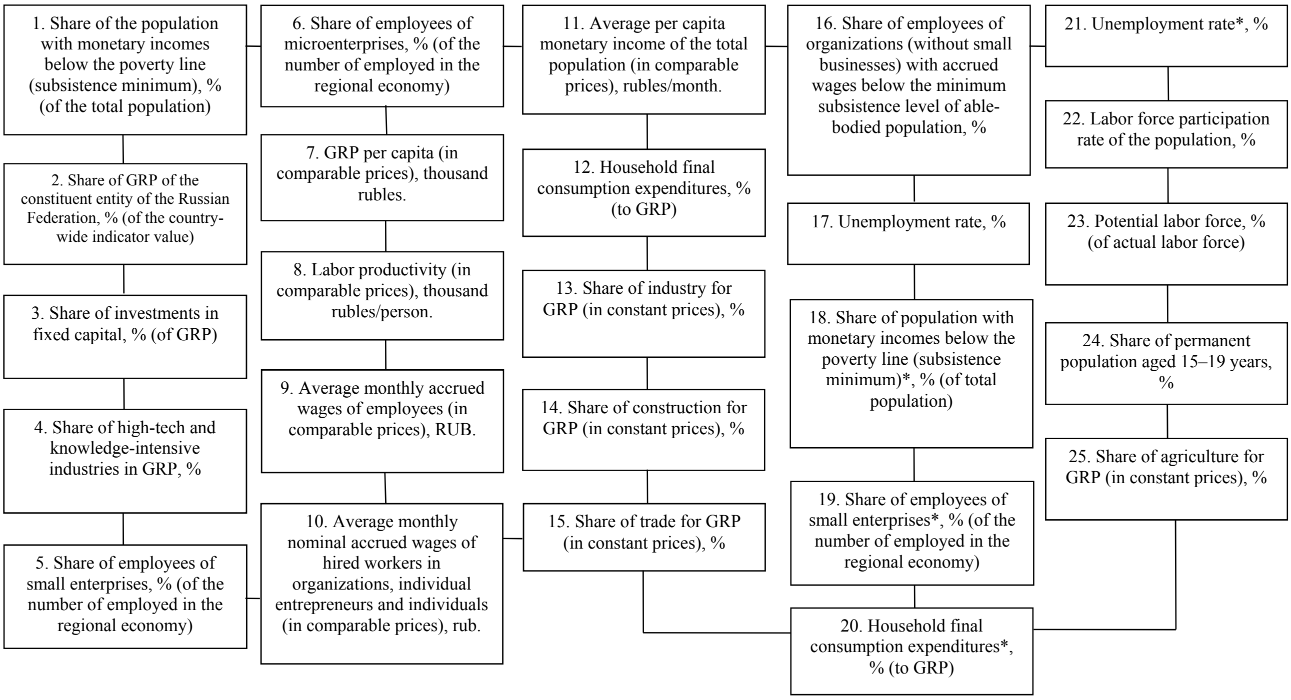

Fig. 5. **Initial system of factors affecting the level of employment in the informal sector of the economy of the constituent entities of the Russian Federation**

Source: compiled by the authors based on [31–36].

into five clusters according to the actual level of employment in the informal sector of the economy.

Returning to the solution of the classification problem, *Fig. 7* visualizes the results of the refined list of key factors affecting the level of employment in the informal sector of the economy of the Russian regions.

According to the data in *Fig. 7,* we can see that in our case, a system of 29 factors is used to solve the problem of classification of RF subjects. Initially, there were 100 factors (25 indicators presented in *Fig. 5* for 4 periods). Hence, most of the factors were eliminated due to their small significance in the formation of the resultant indicator.

In order to evaluate the accuracy of the procedure, a "Confusion Matrix in Multi-class Classification" is constructed (*Fig. 8*).

As shown in *Fig. 8*, in our case, the accuracy of recognizing the objects under study in the context of each class was 100%. This means that the applied modern method of machine learning allows us to correctly identify the cluster of any Russian region in the future, based on the expected level of employment in the informal sector of the economy.

Results

Table 2 presents the main results of clustering. *Fig. 9* visualizes the distribution of Russian regions by the level of employment in the informal sector of the economy.

At different "poles", a relatively small number of regions turned out to be in this distribution.

The most favorable employment situation (low level in the informal sector of the economy) was observed in five subjects of the Russian Federation: the Moscow Region, Moscow, Murmansk Region, St. Petersburg and the Chukotka Autonomous Okrug. According to the cluster profile, the average value of the indicator in the group was 8.3; 7.6; 7.5 and 6.5%, respectively, in 2017, 2019, 2021 and 2023. From the above data, it can be seen that there has been a positive downward trend in the average level of employment in the informal sector of the economy in this group of regions. The least favorable situation for the studied phenomenon has developed in four Russian regions from the North Caucasus Federal District: the Republic of Dagestan, the Republic of Ingushetia, the Kabardino-Balkarian Republic and the Chechen Republic. At the same time, the average level of employment in the informal sector of the economy for this group of regions was 53.3; 52; 50 and 46.1%, respectively, in 2017, 2019, 2021 and 2023. There is also a positive downward trend in the average value of the indicator. According to the results of the cluster analysis, it was found that the largest group of Russian re-

Table 1
Pearson's matrix of values of pairwise correlation coefficients (key fragment)

	Y	**Z_1**	**Z_5**	**Z_6**	**Z_7**	**Z_8**	**Z_9**	**Z_{10}**	**Z_{11}**	**Z_{12}**	**Z_{13}**	**Z_{16}**	**Z_{17}**	**Z_{18}**	**Z_{19}**	**Z_{20}**	**Z_{21}**	**Z_{24}**
Y	1																	
Z_1	0.58	1																
Z_5	−0.57	−0.48	1															
Z_6	−0.49	−0.52	0.69	1														
Z_7	−0.53	−0.49	0.26	0.31	1													
Z_8	−0.47	−0.43	0.22	0.27	0.99	1												
Z_9	−0.57	−0.44	0.08	0.25	0.85	0.82	1											
Z_{10}	−0.60	−0.41	0.14	0.27	0.87	0.84	0.98	1										
Z_{11}	−0.53	−0.70	0.27	0.41	0.80	0.74	0.80	0.79	1									
Z_{12}	0.64	0.33	−0.28	−0.28	−0.78	−0.76	−0.75	−0.78	−0.51	1								
Z_{13}	−0.47	−0.32	0.24	0.12	0.65	0.66	0.54	0.59	0.34	−0.72	1							
Z_{16}	0.51	0.47	−0.17	−0.31	−0.46	−0.46	−0.64	−0.61	−0.40	0.57	−0.42	1						
Z_{17}	0.68	0.73	−0.54	−0.47	−0.38	−0.33	−0.36	−0.35	−0.42	0.39	−0.36	0.49	1					
Z_{18}	0.55	0.99	−0.47	−0.51	−0.48	−0.43	−0.42	−0.40	−0.69	0.32	−0.31	0.45	0.72	1				
Z_{19}	−0.56	−0.49	0.92	0.66	0.28	0.24	0.14	0.18	0.27	−0.32	0.26	−0.27	−0.56	−0.49	1			
Z_{20}	0.64	0.35	−0.29	−0.29	−0.76	−0.75	−0.74	−0.76	−0.50	0.98	−0.71	0.59	0.39	0.33	−0.33	1		
Z_{21}	0.67	0.73	−0.57	−0.48	−0.39	−0.33	−0.33	−0.33	−0.43	0.37	−0.35	0.43	0.98	0.72	−0.59	0.37	1	
Z_{24}	0.54	0.46	−0.71	−0.48	−0.12	−0.07	0.07	0.04	−0.10	0.21	−0.20	0.15	0.63	0.45	−0.67	0.20	0.67	1

Source: Developed by the authors.

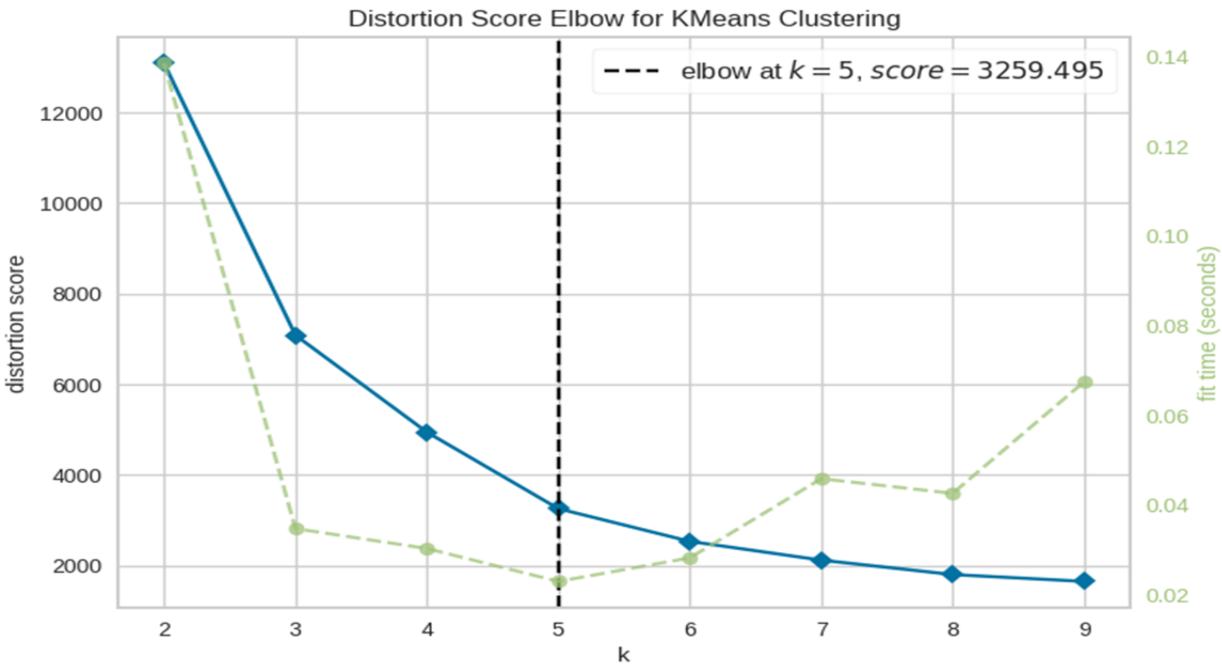

Fig. 6. **Visualization of the results of the elbow method in the Python programming language**

Source: Developed by the authors.

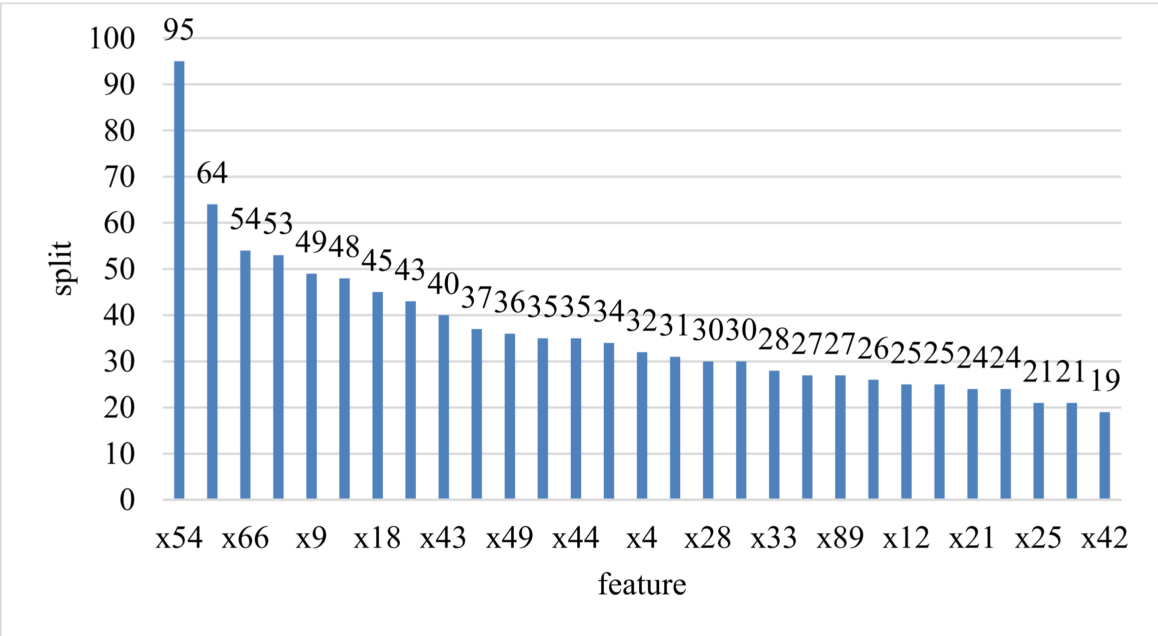

Fig. 7. **Ranked system of key factors determining the level of employment in the informal sector of the economy in Russian regions**

Source: Developed by the authors.

gions (40 or almost half of the total number) were formed by subjects of the Russian Federation with an employment level in the informal sector of the economy below average. In this group, the average value of the indicator was about 18.4–18.8% in 2017, 2019 and 2021. In 2023, there was a slight decrease in the indicator (to 16.6%).

The average level of employment in the informal sector of the economy was observed in 24 Russian regions, including the Republic of Bashkortostan. The average value of the indicator in this group of RF subjects was from the interval from 25.9% to 26.9% in 2017, 2019 and 2021. However, as in the previous cluster, it slightly (to 23.3%)

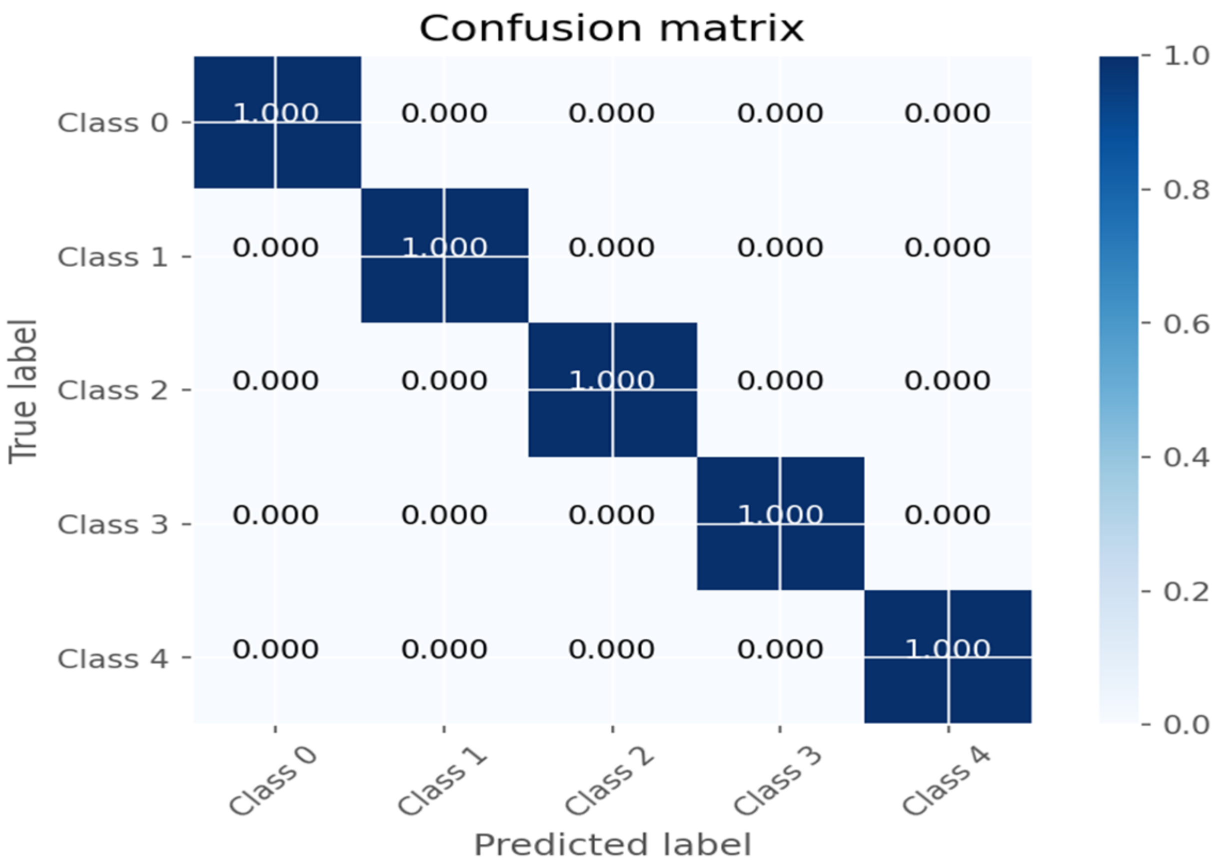

Fig. 8. **"Confusion matrix in multiclass classification" (LightGBM method, Python programming language)**

Source: Developed by the authors.

Fig. 9. **Distribution of Russian regions by level of employment in the informal sector of the economy**

Source: Developed by the authors.

Table 2
Main results of clustering of Russian regions by the level of employment in the informal sector of the economy

Cluster number	Average level of employment in the informal sector of the economy, %				Qualitative characterization of the level of employment in the informal sector of the economy	Cluster size	
	2017	2019	2021	2023		Number of regions. units.	Share of regions, %
The first one	8.3	7.6	7.5	6.5	Low level	5	6.1
Second	18.4	18.8	18.5	16.6	Below average	40	48.8
Third	25.9	26.9	26.2	23.3	Medium level	24	29.2
Fourth	32.2	35.4	35	32.8	Above average	9	11
Fifth	53.3	52	50	46.1	High level	4	4.9

Note: Clustering was carried out for 82 subjects of the Russian Federation. Arkhangelsk and Tyumen oblasts with autonomous okrugs in their composition. Without new regions of Russia (DNR, LNR, Zaporizhzhya and Kherson oblasts) due to the lack of necessary statistical information.

Source: Developed by the authors.

decreased in 2023, which is also characterized positively.

Finally, the group with the level of employment in the informal sector above the average economy included 9 Russian regions. Here, the average value of the indicator was about 35.4 (35)% in 2019 (2021), 32.2–32.8% in 2017 and 2023. As can be seen in 2019 and 2021, there was a slight increase in the level of employment in the informal economy for this group of Russian regions. However, in 2023 the average value of the indicator practically decreased to the level of 2017.

The city of Sevastopol and the Republic of Crimea, which are not represented on the map, were characterized by the average and above average level of employment in the informal sector of the economy, respectively.

Summarizing the results of cluster analysis, it is necessary to note the abnormally high value of employment in the informal sector of the economy in a number of subjects of the Russian Federation. For example, the highest level of employment in the informal sector of the economy among Russian regions in 2021 was recorded in the Republic of Ingushetia (52.7%). According to this indicator, the Russian region is comparable with Colombia (50.5%), Dominican Republic (51.2%), Armenia (51.5%), Iraq and Ethiopia (54.4%), and Mexico (55.2%), i.e. with a number of economically developing countries in Asia, Africa, North and South America [2]. It is necessary to emphasize the high degree of differentiation on the studied phenomenon in the regional context characteristic of modern Russia. Thus, the lowest value of the level of employment in the informal economy among the constituent entities of the Russian Federation in 2021 was recorded in Moscow (4.9%), which is comparable to the value of a similar indicator in such economically developed European countries as Austria, Spain and Finland.

Next, let us move on to the solution of the classification problem. Within the framework of the study we will limit ourselves to assigning two Russian regions from different groups by the level of employment in the informal sector of the economy to a certain cluster (class) in the future. Let us do this on the example of Moscow and the Republic of Bashkortostan for 2025. As previously noted, in 2023, the above two Russian regions were characterized, respectively, by low and medium level of employment in the informal sector of the economy.

The experts make a prospective assessment of key factors (including lag independent variables) based on their actual values for 2017, 2019, 2021, 2023 (taking into account the "lag" effect) (*Table 3*).

In case of development of events in the future according to the experts' scenario, it is expected that the city of Moscow and the Republic of Bashkortostan in 2025 will remain in the same groups (clusters) of Russian regions, i.e., they will

Table 3

Prospective assessment of values of key factor indicators for the city of Moscow and the Republic of Bashkortostan for the year 2025 (2024)

Indicator	Moscow	Republic of Bashkortostan
Population with incomes below the poverty line (subsistence minimum), % (of total population)	4	9
Share of investments in fixed capital*, % (of GRP)	23	25
Share of products of high-tech and knowledge-intensive industries in GRP*, %	25	23
Share of employees of small enterprises, % (of the number of employed)	11	5.5
Share of employees in microenterprises, % (of the number of employed)	15	5
GRP per capita (in comparable prices)*, thousand rubles.	1400	600
Average monthly accrued salary of employees (in comparable prices), rub.	90 000	60 000
Average per capita cash income of the total population (in comparable prices), rub.	95 000	45 000
Household final consumption expenditures*, % (to GRP)	45	80
Share of industry for GRP (in constant prices)*, %	15	31
Share of construction for GRP (in constant prices)*, %	5	7
Labor force participation rate of the population, %	67	59
Potential labor force, % (of actual labor force)	0.3	1

Note: * — prospective assessment of the indicator value is given for 2024.

Source: Developed by the authors.

be characterized, respectively, by a low and medium level of employment in the informal sector of the economy.

Conclusion

According to the results of cluster analysis, we can conclude that modern Russia is characterized by a high degree of differentiation of regions by the level of employment in the informal sector of the economy. In the group of the most favorable subjects of the Russian Federation, the situation with regard to the studied phenomenon is close to the economically developed countries of the West. For the group of Russian regions with the least favorable situation in terms of employment in the informal sector of the economy, the situation is almost identical to that in a number of economically developing countries of the world from Asia, Africa, North and South America. At the same time, for 40 subjects of the Russian Federation (almost half of their total number) the level of the studied phenomenon was below average (about 17–19%), comparable to that in a number of economically developing countries of Eastern Europe such as Bosnia and Herzegovina (18.8%), Serbia (16.9%), Czech Republic (15.3%), etc. [2].

The literature review emphasized the fundamental difference between informal employment in economically developed and developing countries of the world. Only the first group of countries is characterized by relatively good working conditions of informally employed. Given this and the results of the cluster analysis, we can conclude that in modern Russia most of the informally employed do not have good working conditions, and, therefore, need to increase the degree of social protection.

In order to prospectively assess the situation, the study solved the task of classifying Russian regions using a modern method of machine learning. This task is a logical continuation of cluster analysis. Under the influence of a number of key factors, it has specified to which group (class) of RF subjects a certain Russian region will belong in the future. The current situation, taking into account possible changes in the future, does not allow us to make an optimistic forecast about further significant reduction in the level of employment in the informal sector of the economy of the two subjects of the Russian Federation, so it is expected that the city of Moscow and the Republic of Bashkortostan in 2025 will remain in their respective clusters (as well as in 2023). Moscow and the Republic of Bashkortostan in 2025 will remain in the corresponding (as well as in 2023) clusters.

The results of the empirical study can be applied in the course of planning by the federal center of the volume of financial resources for social support of the working population in the informal sector of the economy of the constituent entities of the Russian Federation.

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ABOUT THE AUTHORS / ИНФОРМАЦИЯ ОБ АВТОРАХ

Aleksey Nikolaevich Borisov — Cand. Sci. (Polit.), Head of the UNESCO Department, MGIMO University, Moscow, Russia
Алексей Николаевич Борисов — кандидат политических наук, заведующий кафедрой ЮНЕСКО, МГИМО МИД России, Москва, Россия
https://orcid.org/0009-0006-0739-7444
una@una.ru

Aleksandr Ivanovich Borodin — Doctor of Economics, Professor at the Department of Financial Management, Plekhanov Russian University of Economics, Moscow, Russia
Александр Иванович Бородин — доктор экономических наук, профессор кафедры финансов устойчивого развития, Российский экономический университет имени Г.В. Плеханова, Москва, Россия
https://orcid.org/0000-0002-2872-1008
aib-2004@yandex.ru

Roman Vladimirovich Gubarev — Cand. Sci. (Econ.), Associate Professor of the Department of Economic Theory, Plekhanov Russian University of Economics, Moscow, Russia
Роман Владимирович Губарев — кандидат экономических наук, доцент кафедры экономической теории, Российский экономический университет имени Г.В. Плеханова, Москва, Россия
https://orcid.org/0000-0003-1634-5030
gubarev.roma@yandex.ru

Evgeny Ivanovich Dzuyba — Research associate, Institute of Social and Economic Research of the Ufa Federal Research Centre of the Russian Academy of Sciences (UFRC RAS), Ufa, Russia
Евгений Иванович Дзюба — научный сотрудник, Институт социально-экономических исследований Федерального государственного бюджетного научного учреждения Уфимского федерального исследовательского центра Российской академии наук (УФИЦ РАН), Уфа, Россия
https://orcid.org/0000-0003-2209-2017
Corresponding Author:
intellectRus@yandex.ru

Oksana Mikhaylovna Kulikova — Cand. Sci. (Eng.), Associate Professor of the Department of Economics, Logistics and Quality Management, Siberian State Automobile and Highway University, Omsk, Russia
Оксана Михайловна Куликова — кандидат технических наук, доцент кафедры экономики, логистики и управления качеством, Сибирский государственный автомобильно-дорожный университет, Омск, Россия
https://orcid.org/0000-0001-9082-9848
ya.aaaaa11@yandex.ru

Authors' declared contributions:
Aleksey N. Borisov — general editing of the article, preparation of the literature review.
Aleksandr I. Borodin — international comparisons, translation of article into English.
Roman V. Gubarev — analysis of Russian statistical data.
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