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Assessment of Interregional Inequality in the Russian Federation Based on the Index of Social Well-Being of the Population

Vyacheslav N. BOBKOV
Plekhanov Russian University of Economics
Institute of Economics of the RAS
Moscow, Russian Federation
e-mail: bobkovvn@mail.ru
ORCID: 0000-0001-7364-5297; ResearcherID: U-6527-2019

Roman V. GUBAREV
Plekhanov Russian University of Economics
Moscow, Russian Federation
e-mail: gubarev.roma@yandex.ru
ORCID: 0000-0003-1634-5030; ResearcherID: N-3990-2016

Evgeny I. DZUYBA
Institute of Social and Economic Research of the UFRC of the RAS
Ufa, Russian Federation
e-mail: intellectRus@yandex.ru
ORCID: 0000-0003-2209-2017; ResearcherID: T-5762-2017

Fanil S. FAYZULLIN
Institute of Social and Economic Research of the UFRC of the RAS
Ufa, Russian Federation
e-mail: fayzullin.f@gmail.com
ORCID: 0000-0001-8368-4441; ResearcherID: F-1475-2018

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Abstract. As part of this study, the goal was to develop adequate (high-precision) tools that would allow for not only a retrospective, but also a prospective assessment of interregional inequality in living standards in the Russian Federation based on the index of social well-being of the population, which is the result of a convolution of private indices. At first, a hypothesis was put forward about the possibility of building an adequate prognostic (traditional econometric) model of dependence of per capita average monetary incomes of the population on a group of factors. The information base of the study was exclusively official data of regional statistics for 2020–2022. In the course of empirical research (correlation and regression analysis), three econometric models differing in the number of factors (from 2 to 4) were developed. However, they allow (according to the average approximation error, taking values from the interval from 8.8 to 9.6 % for different econometric models) approximating regional statistics data only with an acceptable degree of accuracy. Next, a similar hypothesis was tested, but involving the use of a different tool (index method in combination with artificial intelligence), which makes it possible to measure the dependence of the population's standard of living on a group of factors. In the course of neuromodelling it was found that any of the 5 artificial neural networks included in the Bayesian ensemble allowed approximating the regional statistics data with a high degree of accuracy (with an average error from 2.8 to 3.9 %). Thus, the second hypothesis can be considered confirmed. As part of the study, the predictive function was implemented by forming a Bayesian ensemble of artificial neural networks. The obtained results of the empirical study can act as a scientific basis for adjusting (updating) the socio-economic policy of regulating the quality and standard of living of the population and its interregional inequality among the constituent entities of the Russian Federation.

Key words: regions of Russia, interregional inequality, standard of living, cash income, index method, correlation-regression analysis, artificial intelligence, forecasting.

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Introduction

Currently, Russia is actively involved in the implementation of the UN international program "Sustainable Development Goals". The tenth goal is to reduce social inequality. There are several types of social inequality. In this study, we will limit ourselves to studying monetary (income) inequality.

Based on statistical data, let us briefly describe the level of income inequality in modern Russia. For example, the income ratio of the richest 10% to the poorest 10% (R/P 10%) assumed an almost identical value of the order (14) in both 2000 and 2022. In 2023, R/P 10% in Russia was 14.8, which is slightly lower than in 2015 (15.5). However, even now (in 2023) R/P 10% in some regions of Russia is significantly higher than the national average. So, in particular, in the Nenets Autonomous Area the value is 19.3, in the Republic of Adygea – 15.5, in the Krasnodar Territory – 15.7, in the Tyumen Region with the Autonomous Area – 19.2 (due to the abnormally high value of R/P 10% in the Yamal-Nenets Autonomous Area – 22.8), in the Republic of Sakha (Yakutia) – 16.1, in the Magadan and Sakhalin regions – 15.5 / 15.6 and, finally, in the Chukotka Autonomous Area – 17.3.

The value of the decile coefficient in 2015–2019 and 2021 in Russia was about 7–7.2. In 2022 and 2023 the ratio of minimum incomes of the richest 10% to maximum incomes of the poorest 10% of Russians assumed lower values: 6.6 and 6.8, respectively. However, at present (in 2023) in some regions (their list is almost identical to the above), the value of the decile coefficient, as well as R/P 10%, was significantly higher than the national average.

A number of other indicators also show significant polarization of Russian society in terms of money income at the current stage of the country's development. For example, in 2023 the average per capita money income of citizens from the first group (5.5%) amounted to 14,564 rubles, while citizens from the fifth group (46.4% of the total money income) received 123,349 rubles, i.e. almost 8.5 times more. At the same time, it is necessary to note a very high degree of concentration of persons with the highest money incomes (5th group) in the capital. Thus, about 43.3% of the all-Russian value of the indicator fell on Moscow; and taking into account Saint Petersburg, the value exceeded 50%.

Thus, we can conclude that smoothing interregional monetary inequality in modern Russia is an important area of state social policy. The development of this direction in the face of several negative external factors, in particular sanctions pressure on the national economy from the United States and the European Union countries, requires adequate tools for monitoring the situation.

In this regard, the aim of our research is to assess interregional inequality in the Russian Federation according to the social well-being index, using artificial intelligence. Such an adequate (high-precision) method of economic and mathematical modeling allows for not only a retrospective, but also a long-term assessment of the phenomenon in question. To achieve the goal, the following tasks were solved:

– an analysis of interregional inequality in terms of living standards was carried out;

– methodological tools for assessing interregional inequality according to the index of social well-being were developed;

– regions were grouped according to the social well-being index, and a forecast was formed.

The object of this study is constituent entities of the Russian Federation. The subject of the study is measurement of the standard of living of their population.

The achievement of the set goal and the solution of tasks predetermined the structure of the work: first, the conceptual framework is clarified, then a thematic empirical study is conducted.

Literature review

Complexity of the terms "quality of life" and "standard of living" has led to the emergence of many different interpretations; a successful attempt at classifying (systematizing) them was made in the work (Spiridonov, Naidenova, 2024). According to the authors of the above-mentioned scientific article, through the prism of the categories "needs", "interests" and "values", all the variety of interpretations can be combined into three approaches: 1) basic approach thattakes into account needs (N-approach); 2) axiological approach that takes into account values (V-approach); 3) synthesis of the first two approaches (NV-approach). The authors of this study, regarding the interpretation of the definitions of "quality of life" and "standard of living", adhere to the basic approach (based on needs). In turn, meeting the needs of population presupposes the availability of various sources of money income (including wages).

While analyzing the effectiveness of executive authorities at the meso-level of management, monetary inequality of the Russian population is estimated through the growth rates of real money incomes and real average monthly wages[1]. This makes it possible to use the managerial factor in regulating socio-economic inequality in Russia

[1] On evaluating the effectiveness of activities of senior officials of constituent entities of the Russian Federation and activities of executive bodies of constituent entities of the Russian Federation: Presidential Decree 68, dated February 4, 2021.

(Merzlyakov, Bogdanov, 2022). However, these indicators, through the dynamics of comparable prices, take into account changes in per capita income and wages only within regions. If they are used to measure interregional inequality, then its level will not reflect interregional differences in living standards, since it does not take into account different purchasing power of the population in Russian regions.

The importance of taking into account differences in the purchasing power of the population to ensure the correctness of interregional comparisons is evidenced by a number of works (Bobkov, Odintsova, 2020, pp. 179–182; Surinov, Luppov, 2022; Bobkov, Gulyugina, 2023).

According to the author's definition, the purchasing power of the population in terms of income and wages is the number of sets of subsistence minimum / consumer baskets (on average per capita, working-age population), falling on a given amount of per capita money income, wages. This indicator measures the standard of living, i.e. current consumption[2] (Bobkov, Gulyugina, 2023). Accordingly, the interregional inequality of the purchasing power of the population in terms of money income measures the gaps in the average standard of living among the population of Russian regions[3].

[2] It represents the number of sets of subsistence minimum / consumer baskets (on average per capita, working-age population, pensioners, children, respectively), falling on a given amount of money income, consumer spending or available household resources.

[3] Rosstat does not calculate the indicator "purchasing power of the population". In contrast to this indicator, it calculates the purchasing power of the average per capita money income of the population through the commodity equivalent of the average per capita money income of the population per month (average monthly nominal accrued wages, average size of assigned pensions), which refers to the amount of any one product (service) with specific consumer properties, which can be purchased provided that the entire amount of money income will be used only for these purposes. Source: Social status and standard of living of the Russian population 2023. Rosstat. Available at: https://rosstat.gov.ru/folder/210/document/13212 (accessed: June 6, 2024).

Based on the works (Ibragimova, Frants, 2020; Dorofeev, 2021; Shatalova, Kasatkina, 2022, etc.), we can conclude that social inequality in income and wealth in Russia (resource inequality) and abroad is usually estimated using several indicators (coefficients or indices): Gini coefficient, R/P 10%, decile coefficient, generalized entropy measures, Theil T and L indices, as well as the family of Atkinson inequality indices. We agree with (Ibragimova, Frants, 2020, p. 77) who point out that the most common indicator of income and wealth inequality is the Gini coefficient. In addition, researchers in the above-mentioned work used the Theil T and L indices and the Atkinson indices to study the contribution of inequality of opportunity to income and wage inequality in the Russian Federation.

The need to make more accurate measurements has led to the use of the index method in interregional comparisons, in which the integral indicator (index) includes several private indices. The work (Simionesku et al., 2020), uses an integral index to assess regional personnel differentiation, taking into account six basic components (private indices) of the labor potential of RF constituent entities: 1) duration of working life; 2) level of labor activity of the population; 3) level of professional training of the employed population; 4) real volume of capital equipment per unit of labor; 5) average per capita gross regional product and 6) average monthly wage of employees. Based on this list, we can conclude that researchers are studying several types of social inequalities simultaneously (in particular, in terms of employment, income, and education level).

Currently, the results obtained with the use of the index method can be significantly supplemented by the use of artificial intelligence or machine learning methods. In particular, Random Forest data mining technique (see, for example, Breiman, 2001) makes it possible to identify hidden interdependencies between various indicators (Zarova, Dubravskaya, 2020), examining the impact of economic indicators on the level of informal employment in Russian regions.

We should note that recently works have begun to appear that are not limited to a retrospective assessment of the phenomenon under consideration using the index method. They conduct a multidimensional cluster analysis that complements the results of rating RF constituent entities, and such an analysis is carried out using various methods of artificial intelligence (AI). For example, the study (Leonidova et al., 2022) measures income inequality in Russian regions with the help of artificial intelligence. A multidimensional cluster analysis is carried out on five particular indicators: 1) average per capita money income; 2) average monthly nominal accrued wages; 3) number of people with incomes below the subsistence minimum; 4) Gini coefficient and 5) R/P 10%. Hierarchical arrangement (see, for example, Shetty, Singh, 2021) of RF constituent entities into a cluster according to the studied phenomenon is performed using Ward's method and Orange Library of machine learning of the Python programming language. However, there are still practically no articles by Russian scientists that implement a predictive function based on AI. At the same time, there are quite a lot of foreign works that use artificial neural networks for the prospective assessment of socio-economic characteristics of various systems (Qiu et al., 2019; Jin et al., 2022; Zhang et al., 2022, etc.).

Data and research methods

This study combines the index method and the use of artificial intelligence to determine the standard of living index, which the authors called ***social well-being index***. Interregional inequality regarding living standards was assessed according to this index. The results of the study complement the methods of assessing the standard of living and its interregional comparisons. The retrospective assessment is deepened by clustering Russia's regions according to the social well-being index of. The forecast function of the dynamics of the above index is also implemented.

According to the hypothesis of our study, the social well-being index helps to measure the standard of living more accurately. This implies a fairly logical definition of interregional inequality in the standard of living. The tasks (clustering and forecasting) in the framework of the work were solved using artificial intelligence (artificial neural networks). All these elements constitute the novelty of the research.

In the framework of the study, an attempt was made to combine the assessment of living standards in the social well-being index of the region through a convolution of private indices, in the center of which is the index of the purchasing power of wages, supplemented by a number of others, with the use of artificial intelligence capable of providing high accuracy approximation of the initial data of regional statistics and subsequent forecasting. The social well-being index obtained in such a combined way is used as the basis for identifying and forecasting interregional inequality in the standard of living. We believe that the definition of social well-being index can be one of the adequate tools for monitoring the current situation related to the standard of living, forecasting possible changes and reducing its interregional gaps. In this study, taking into account the above approaches to determining indicators for studying the standard of living, an attempt is made to propose an adequate (high-precision) econometric model of its assessment and application for interregional comparisons using successive iterations. Initially, taking into account case studies (Ibragimova, Frants, 2020; Zhitin, Prokofev, 2022), we propose the following system of factor indicators:

1) average monthly nominal accrued wages of employees of organizations (X_1), rubles;

2) number of employees per pensioner (X_2), people;

Table 1. Matrix of paired Pearson correlation coefficients

Indicator	Y	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8
Y	1								
X_1	0.920	1							
X_2	0.679	0.608	1						
X_3	0.649	0.517	0.637	1					
X_4	0.573	0.480	0.684	0.842	1				
X_5	-0.560	-0.358	-0.309	-0.642	-0.336	1			
X_6	0.478	0.437	0.397	0.637	0.457	-0.554	1		
X_7	0.306	0.251	0.432	0.097	0.181	-0.085	0.084	1	
X_8	0.181	0.158	0.051	0.253	0.060	-0.198	0.108	0.018	1
Source: own elaboration.									

3) employment rate of the population aged 15–72 years (X_3), %;

4) level of participation of the population aged 15–72 years in labor force (X_4), %;

5) share of the population with money incomes below the subsistence minimum / poverty line, 2021–2022 (X_5), %;

6) proportion of urban population (X_6), %;

7) proportion of the employed population with higher education (X_7), %;

8) proportion of individual entrepreneurs (X_8), %.

Let us estimate the impact of each of the factors on the resulting indicator (Y, average per capita money income of the population) based on the calculation and analysis of paired Pearson correlation coefficients according to regional statistics for 2015–2022[4] (*Tab. 1*).

The first factor has a strong impact on the resulting indicator. Between the group of factors (from the second to the sixth) and the resulting indicator, there is a direct (with the exception of the fifth factor) relationship of average strength. Finally, the seventh and eighth factors have little effect on the resulting indicator; therefore, it is impractical to include them in the model. We should note that the third and fourth factors are strongly related, but the value of their paired Pearson correlation coefficient does not exceed 0.85. Hence, there is no multicollinearity in the initial data; thus, a system of the first six factors can be used to form a number of econometric models. According to the results of the correlation and regression analysis, the third and sixth factors were excluded. The parameter of the regression equation for the third factor turned out to be insignificant. In addition, the above factors had an incorrect (negative) sign in the regression equation, contradicting the socio-economic meaning. The results of checking econometric models for adequacy (accuracy of approximation of the initial data) are presented in *Table 2.*

Table 2. Assessment of econometric adequacy of the models

Model	Regression equation	R^2	Normalized R^2	E, %
First	$Y=-1916.4+0.504X_1+5428.3X_2+188.8X_4-591X_5$	0.924	0.923	8.8
Second	$Y=8469.2+0.506X_1+7068.2X_2-609.2X_5$	0.922	0.922	8.9
Third	$Y=17523.4+0.567X_1-648.8X_5$	0.907	0.907	9.6
Source: own elaboration.				

[4] Regions of Russia. Socio-economic indicators. 2023: Statistics collection. Moscow: Rosstat.

According to the value of determination coefficients (exceeding 0.9), each of the three econometric models allows forecasting the value of the resulting indicator with a high degree of accuracy. However, based on the mean approximation error (E), which takes values of more than 8%, all models provide only acceptable forecast accuracy. Therefore, further in the framework of the study, in order to build a high-precision model assessing the social well-being of the population of RF constituent entities, an index method is used in combination with artificial intelligence. The resulting index is the social well-being index. Taking into account the results of the previously conducted correlation and regression analysis, the indices of the first six factor indicators are private. The social well-being index is calculated under the following basic conditions.

1. All private indexes are considered equivalent. "Convolution" is carried out using a simple arithmetic mean formula.

2. We take into account the need to subordinate the initial information to the law of normal distribution, i.e. the asymmetry should not exceed 0.5. In order to reduce the value of the indicator (if necessary), the procedure for transforming the initial information is applied (the root of the second or third degree is extracted from the normalized values of private indicators)[5].

3. Normalization of the values of private indicators is carried out in the maximum way. At the same time, the scope of variation is determined in the yearly context.

4. Growth of the values of private indicators in dynamics is a positive trend, with the exception of the fifth factor.

5. The first factor in the calculations appears in comparable prices for all regions of Russia. The cost of a fixed set of consumer goods and services in Moscow is taken as the base of comparison; correction coefficients are introduced for RF constituent entities. As a result, the first private index is index of the purchasing power of the region's population according to the average monthly nominal accrued wages of employees of organizations. It has the strongest influence on the integral index of social well-being, which, as a result of the transformations carried out, represents the author's integral index of the standard of living of the region's population.

Research results

The results of calculating the social well-being index and a subsequent ranking of Russia's regions are presented in *Table 3.*

Table 3. Index / rating of social well-being of the population of RF constituent entities

RF constituent entity	Index value (*y*) / Rank according to value *y*							
	2015	2016	2017	2018	2019	2020	2021	2022
Belgorod Region	0.613/ 29	0.627/ 21	0.649/ 19	0.602/ 21	0.606/ 19	0.641/ 15	0.638/ 21	0.642/ 19
Bryansk Region	0.512/ 61	0.511/ 60	0.516/ 58	0.451/ 60	0.453/ 62	0.466/ 62	0.482/ 63	0.469/ 67
Vladimir Region	0.598/ 32	0.573/ 34	0.597/ 32	0.530/ 39	0.556/ 33	0.569/ 32	0.581/ 33	0.620/ 25
Voronezh Region	0.557/ 47	0.555/ 46	0.583/ 37	0.532/ 37	0.544/ 35	0.568/ 33	0.589/ 30	0.597/ 30
Ivanovo Region	0.560/ 45	0.548/ 51	0.585/ 35	0.484/ 52	0.497/ 48	0.494/ 51	0.557/ 40	0.559/ 41

[5] Abashkin V.L., Abdrakhmanova G.I., Bredikhin S.V. et al. (2023). The rating of innovative development of constituent entities of the Russian Federation. Issue 8. Moscow: Higher School of Economics. P. 52.

Continuation of Table 3

RF constituent entity	Index value (*y*) / Rank according to value *y*							
	2015	2016	2017	2018	2019	2020	2021	2022
Kaluga Region	0.656/ 18	0.662/ 14	0.674/ 14	0.644/ 13	0.628/ 14	0.656/ 14	0.677/ 13	0.666/ 16
Kostroma Region	0.527/ 58	0.534/ 56	0.550/ 54	0.472/ 55	0.487/ 52	0.502/ 48	0.508/ 54	0.500/ 58
Kursk Region	0.566/ 43	0.560/ 43	0.579/ 40	0.521/ 41	0.534/ 39	0.543/ 41	0.578/ 34	0.568/ 37
Lipetsk Region	0.589/ 34	0.594/ 28	0.619/ 26	0.573/ 27	0.580/ 26	0.606/ 23	0.609/ 27	0.617/ 26
Moscow Region	0.734/ 8	0.733/ 7	0.763/ 7	0.747/ 7	0.737/ 7	0.740/ 7	0.738/ 9	0.728/ 8
Orel Region	0.484/ 67	0.481/ 67	0.486/ 67	0.405/ 69	0.382/ 73	0.414/ 70	0.433/ 70	0.417/ 71
Ryazan Region	0.475/ 68	0.483/ 65	0.509/ 61	0.422/ 65	0.472/ 56	0.462/ 63	0.471/ 65	0.496/ 59
Smolensk Region	0.573/ 39	0.550/ 49	0.577/ 41	0.504/ 46	0.463/ 59	0.491/ 54	0.510/ 53	0.540/ 46
Tambov Region	0.499/ 63	0.491/ 63	0.513/ 60	0.434/ 64	0.442/ 65	0.480/ 56	0.491/ 62	0.506/ 57
Tver Region	0.607/ 30	0.590/ 29	0.618/ 28	0.573/ 26	0.573/ 28	0.586/ 28	0.585/ 32	0.587/ 34
Tula Region	0.613/ 28	0.612/ 26	0.625/ 24	0.576/ 25	0.585/ 25	0.616/ 21	0.626/ 24	0.629/ 21
Yaroslavl Region	0.670/ 13	0.648/ 17	0.655/ 17	0.604/ 20	0.590/ 23	0.614/ 22	0.641/ 20	0.628/ 22
Moscow	0.905/ 1	0.920/ 1	0.925/ 1	0.942/ 1	0.922/ 1	0.934/ 1	0.957/ 1	0.928/ 1
Republic of Karelia	0.505/ 62	0.514/ 59	0.508/ 64	0.448/ 61	0.473/ 55	0.477/ 59	0.475/ 64	0.467/ 68
Komi Republic	0.643/ 20	0.615/ 25	0.603/ 31	0.564/ 28	0.559/ 32	0.553/ 38	0.546/ 44	0.530/ 49
Arkhangelsk Region	0.562/ 44	0.547/ 53	0.573/ 43	0.511/ 44	0.513/ 42	0.515/ 47	0.540/ 46	0.527/ 51
Vologda Region	0.570/ 41	0.577/ 33	0.560/ 49	0.493/ 48	0.510/ 44	0.544/ 40	0.523/ 50	0.530/ 50
Kaliningrad Region	0.662/ 16	0.638/ 19	0.639/ 21	0.586/ 24	0.600/ 21	0.597/ 26	0.610/ 25	0.624/ 24
Leningrad Region	0.651/ 19	0.641/ 18	0.673/ 15	0.615/ 17	0.607/ 18	0.625/ 19	0.642/ 19	0.697/ 12
Murmansk Region	0.739/ 7	0.731/ 8	0.745/ 8	0.707/ 8	0.707/ 8	0.707/ 9	0.748/ 7	0.728/ 9
Novgorod Region	0.604/ 31	0.586/ 30	0.592/ 33	0.523/ 40	0.511/ 43	0.493/ 53	0.545/ 45	0.531/ 48
Pskov Region	0.491/ 66	0.489/ 64	0.471/ 69	0.416/ 67	0.451/ 63	0.439/ 66	0.497/ 59	0.478/ 63
Saint Petersburg	0.850/ 3	0.856/ 3	0.882/ 2	0.880/ 2	0.858/ 3	0.879/ 2	0.906/8 3	0.893/ 3
Republic of Adygea	0.347/ 80	0.302/ 80	0.309/ 80	0.279/ 77	0.333/ 76	0.363/ 75	0.305/ 77	0.323/ 77
Republic of Kalmykia	0.387/ 77	0.406/ 73	0.410/ 76	0.328/ 76	0.321/ 77	0.375/ 74	0.349/ 74	0.377/ 73

Continuation of Table 3

RF constituent entity	Index value (*y*) / Rank according to value *y*							
	2015	2016	2017	2018	2019	2020	2021	2022
Republic of Crimea	0.426/ 74	0.388/ 75	0.439/ 73	0.363/ 74	0.413/ 68	0.438/ 67	0.442/ 69	0.432/ 70
Krasnodar Region	0.539/ 54	0.540/ 54	0.563/ 46	0.514/ 43	0.515/ 41	0.538/ 42	0.548/ 43	0.549/ 43
Astrakhan Region	0.614/ 27	0.585/ 31	0.630/ 23	0.541/ 35	0.537/ 38	0.554/ 37	0.563/ 39	0.581/ 35
Volgograd Region	0.577/ 37	0.564/ 40	0.575/ 42	0.540/ 36	0.525/ 40	0.556/ 36	0.575/ 35	0.597/ 29
Rostov Region	0.529/ 57	0.548/ 52	0.553/ 53	0.492/ 49	0.498/ 47	0.532/ 43	0.550/ 42	0.566/ 38
Sevastopol	0.617/ 25	0.566/ 37	0.606/ 30	0.608/ 19	0.614/ 16	0.605/ 24	0.652/ 15	0.667/ 14
Republic of Dagestan	0.413/ 75	0.405/ 74	0.411/ 75	0.337/ 75	0.354/ 75	0.321/ 77	0.310/ 76	0.352/ 74
Republic of Ingushetia	0.369/ 78	0.372/ 76	0.444/ 72	0.386/ 72	0.396/ 70	0.391/ 71	0.346/ 75	0.344/ 75
Kabardino-Balkarian Republic	0.471/ 69	0.440/ 72	0.450/ 71	0.421/ 66	0.414/ 67	0.440/ 65	0.462/ 66	0.471/ 66
Karachay-Cherkess Republic	0.311/ 81	0.281/ 81	0.263/ 81	0.219/ 81	0.218/ 81	0.235/ 82	0.255/ 81	0.282/ 80
Republic of North Ossetia-Alania	0.465/ 71	0.440/ 71	0.487/ 66	0.473/ 54	0.379/ 74	0.323/ 76	0.379/ 73	0.409/ 72
Chechen Republic	0.409/ 76	0.366/ 78	0.350/ 78	0.265/ 78	0.281/ 78	0.263/ 81	0.276/ 80	0.269/ 81
Stavropol Territory	0.513/ 60	0.509/ 61	0.509/ 62	0.456/ 59	0.482/ 53	0.498/ 50	0.500/ 57	0.509/ 56
Republic of Bashkortostan	0.552/ 51	0.548/ 50	0.557/ 50	0.480/ 53	0.474/ 54	0.493/ 52	0.507/ 55	0.521/ 53
Republic of Mari El	0.518/ 59	0.495/ 62	0.496/ 65	0.394/ 70	0.428/ 66	0.422/ 69	0.446/ 68	0.448/ 69
Republic of Mordovia	0.557/ 46	0.558/ 44	0.556/ 52	0.461/ 58	0.510/ 45	0.472/ 61	0.521/ 51	0.562/ 39
Republic of Tatarstan	0.715/ 9	0.705/ 9	0.716/ 9	0.671/ 10	0.667/ 10	0.690/ 11	0.710/ 10	0.715/ 10
Udmurt Republic	0.639/ 21	0.619/ 23	0.619/ 27	0.557/ 31	0.541/ 36	0.570/ 31	0.571/ 36	0.560/ 40
Chuvash Republic	0.570/ 42	0.530/ 57	0.520/ 57	0.448/ 62	0.456/ 61	0.474/ 60	0.494/ 61	0.488/ 61
Perm Territory	0.578/ 36	0.571/ 35	0.562/ 47	0.493/ 47	0.498/ 46	0.531/ 44	0.552/ 41	0.541/ 45
Kirov Region	0.554/ 49	0.553/ 48	0.567/ 44	0.509/ 45	0.488/ 51	0.519/ 46	0.527/ 49	0.523/ 52
Nizhny Novgorod Region	0.663/ 15	0.667/ 12	0.685/ 12	0.636/ 14	0.636/ 13	0.662/ 13	0.673/ 14	0.679/ 13
Orenburg Region	0.556/ 48	0.554/ 47	0.567/ 45	0.517/ 42	0.458/ 60	0.483/ 55	0.496/ 60	0.472/ 65
Penza Region	0.553/ 50	0.561/ 41	0.529/ 56	0.492/ 50	0.469/ 57	0.478/ 57	0.530/ 48	0.481/ 62
Samara Region	0.675/ 12	0.666/ 13	0.665/ 16	0.626/ 15	0.611/ 17	0.637/ 16	0.650/ 16	0.656/ 17

RF constituent entity	Index value (*y*) / Rank according to value *y*							
	2015	2016	2017	2018	2019	2020	2021	2022
Saratov Region	0.551/ 52	0.536/ 55	0.515/ 59	0.446/ 63	0.495/ 50	0.499/ 49	0.514/ 52	0.547/ 44
Ulyanovsk Region	0.550/ 53	0.557/ 45	0.557/ 51	0.466/ 57	0.466/ 58	0.477/ 58	0.504/ 56	0.532/ 47
Kurgan Region	0.429/ 73	0.368/ 77	0.367/ 77	0.258/ 79	0.264/ 79	0.309/ 78	0.277/ 79	0.284/ 79
Sverdlovsk Region	0.681/ 11	0.651/ 16	0.651/ 18	0.591/ 23	0.604/ 20	0.617/ 20	0.642/ 18	0.625/ 23
Tyumen Region	0.763/ 5	0.761/ 5	0.777/ 5	0.761/ 6	0.747/ 6	0.748/ 6	0.760/ 6	0.749/ 6
Chelyabinsk Region	0.665/ 14	0.656/ 15	0.682/ 13	0.661/ 12	0.661/ 11	0.673/ 12	0.684/ 12	0.666/ 15
Altai Republic	0.351/ 79	0.327/ 79	0.324/ 79	0.241/ 80	0.260/ 80	0.301/ 79	0.282/ 78	0.254/ 82
Republic of Tyva	0.191/ 82	0.251/ 82	0.240/ 82	0.218/ 82	0.209/ 82	0.290/ 80	0.244/ 82	0.291/ 78
Republic of Khakassia	0.530/ 55	0.515/ 58	0.531/ 55	0.467/ 56	0.447/ 64	0.437/ 68	0.498/ 58	0.510/ 55
Altai Territory	0.495/ 65	0.468/ 69	0.468/ 70	0.378/ 73	0.395/ 71	0.387/ 72	0.407/ 71	0.474/ 64
Krasnoyarsk Territory	0.498/ 64	0.483/ 66	0.508/ 63	0.594/ 22	0.595/ 22	0.600/ 25	0.633/ 23	0.612/ 28
Irkutsk Region	0.595/ 33	0.583/ 32	0.581/ 39	0.531/ 38	0.540/ 37	0.546/ 39	0.565/ 38	0.587/ 33
Kemerovo Region	0.616/ 26	0.609/ 27	0.610/ 29	0.543/ 34	0.555/ 34	0.565/ 34	0.571/ 37	0.572/ 36
Novosibirsk Region	0.624/ 23	0.627/ 20	0.638/ 22	0.564/ 29	0.577/ 27	0.579/ 30	0.610/ 26	0.596/ 31
Omsk Region	0.629/ 22	0.616/ 24	0.620/ 25	0.563/ 30	0.563/ 30	0.594/ 27	0.596/ 29	0.592/ 32
Tomsk Region	0.530/ 56	0.566/ 38	0.561/ 48	0.552/ 32	0.560/ 31	0.562/ 35	0.586/ 31	0.557/ 42
Republic of Buryatia	0.471/ 70	0.442/ 70	0.428/ 74	0.405/ 68	0.384/ 72	0.384/ 73	0.381/ 72	0.331/ 76
Republic of Sakha (Yakutia)	0.588/ 35	0.561/ 42	0.585/ 36	0.615/ 16	0.622/ 15	0.629/ 17	0.637/ 22	0.635/ 20
Trans-Baikal Territory	0.576/ 38	0.568/ 36	0.581/ 38	0.487/ 51	0.496/ 49	0.521/ 45	0.533/ 47	0.520/ 54
Kamchatka Territory	0.702/ 10	0.678/ 10	0.686/ 11	0.675/ 9	0.694/ 9	0.723/ 8	0.739/ 8	0.735/ 7
Primorye Territory	0.623/ 24	0.626/ 22	0.645/ 20	0.610/ 18	0.589/ 24	0.628/ 18	0.648/ 17	0.648/ 18
Khabarovsk Territory	0.656/ 17	0.676/ 11	0.701/ 10	0.669/ 11	0.638/ 12	0.697/ 10	0.699/ 11	0.705/ 11
Amur Region	0.573/ 40	0.564/ 39	0.592/ 34	0.550/ 33	0.564/ 29	0.585/ 29	0.599/ 28	0.615/ 27
Magadan Region	0.842/ 4	0.824/ 4	0.868/ 4	0.863/ 4	0.836/ 4	0.876/ 4	0.912/ 2	0.897/ 2
Sakhalin Region	0.746/ 6	0.747/ 6	0.769/ 6	0.783/ 5	0.765/ 5	0.787/ 5	0.796/ 5	0.809/ 5

End of Table 3

RF constituent entity	Index value (*y*) / Rank according to value *y*							
	2015	2016	2017	2018	2019	2020	2021	2022
Jewish Autonomous Region	0.464/ 72	0.469/ 68	0.475/ 68	0.394/ 71	0.412/ 69	0.456/ 64	0.451/ 67	0.488/ 60
Chukotka Autonomous Area	0.861/ 2	0.863/ 2	0.876/ 3	0.875/ 3	0.866/ 2	0.877/ 3	0.882/ 4	0.877/ 4
Miny	0.191	0.251	0.240	0.218	0.209	0.235	0.244	0.254
Maxy	0.905	0.920	0.925	0.942	0.922	0.934	0.957	0.928
Note: The Arkhangelsk Region is considered with the Nenets Autonomous Area, and the Tyumen Region with the Khanty-Mansi Autonomous Area – Yugra and the Yamal-Nenets Autonomous Area. Source: own elaboration.								

The coefficient of interregional differentiation of the social well-being index (calculated as the ratio of the highest index value to the lowest) was 4.74 times in 2015, 3.67 times in 2016, 3.85 times in 2017, 4.32 times in 2018, 4.41 times in 2019, 3.97 times in 2020, 3.92 times in 2021, and 3.65 times in 2022. In 2019–2022, the differentiation of RF constituent entities according to the social well-being index decreased. In 2022, compared with 2015, the coefficient value decreased 1.3-fold.

The leaders of the rating (top five) in the analyzed period were Moscow, Saint Petersburg, the Magadan Region, the Chukotka Autonomous Area, and the Sakhalin Region. Here we should note that throughout the analyzed period, even the undisputed leader of the rating – Moscow – had an index value of less than 1; therefore, the capital city is not the absolute leader, i.e. the leader in all six private indices at the same time. The outsiders of the rating (bottom five) included on a regular basis the Chechen Republic, the Karachay-Cherkess Republic, the Altai Republic, the Kurgan Region and the Republic of Tyva.

Further, using the example of 2020–2022, clustering of RF constituent entities according to the social well-being index using artificial intelligence is carried out. Cluster analysis is carried out by the method of Kohonen Self-Organizing Maps in a demo version of Deductor Studio Lite 5.1. The training of each such map is carried out under the following basic conditions: 1) initialization method is training set; 2) Gaussian neighborhood function. Based on the calculation and analysis of the highest and lowest values of the index, a decision was made on the expediency of allocating four clusters of Russian regions characterized by high, above median, median and below median levels of social well-being. The results of annual distribution of RF constituent entities according to y are shown in *Figure 1.*

Table 4. Cluster structure of RF constituent entities according to the social well-being index

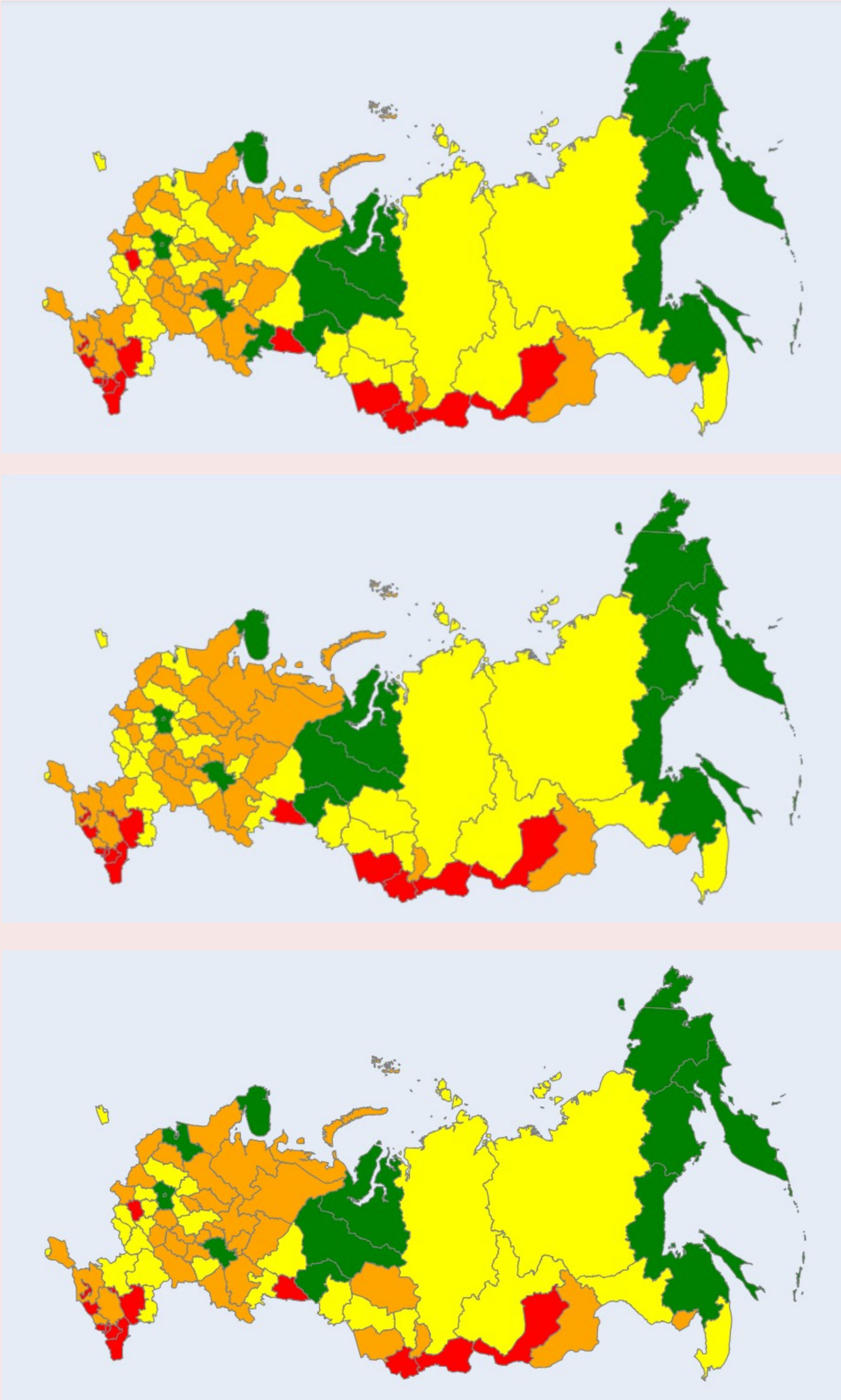
Cluster	2020		2021		2022	
	Number of regions	%	Number of regions	%	Number of regions	%
First	12	14.6	11	13.4	12	14.6
Second	29	35.4	28	34.1	26	31.7
Third	28	34.1	31	37.8	32	39.0
Fourth	13	15.9	12	14.6	12	14.6
Source: own elaboration.						

Figure 1. Distribution of RF constituent entities according to the social well-being index in 2020 (a), 2021 (b), 2022 (c)

a)

b)

c)



Note:

first cluster | second cluster | third cluster | fourth cluster

Source: own elaboration.

Next, let us analyze changes in the cluster structure of Russian regions (*Tab. 4*). Most (about 70–72%) of the country's constituent entities in 2020–2022 were characterized by either above median or median levels of the social well-being index. At the same time, regions with high and below median levels of the social well-being index were located annually at different "poles" (approximately 13–15%).

It is necessary to note the stability of the formed cluster structure of RF constituent entities over the past three years of the period under consideration. The number of regions in both the first and fourth clusters remained almost unchanged. Insignificant (in terms of number) transitions of Russian regions were observed only between the second and third clusters.

The correctness of the procedure (cluster analysis using artificial intelligence) is confirmed by a number of indicators (*Tab. 5*).

All observations were fully recognized annually. The stability of the obtained results is also indicated by the same order of both the mean and maximum errors in 2020–2022. Next, the predictive function is also implemented using artificial intelligence in the demo version of Deductor Studio Lite 5.1. Due to the limitation in the number of observations (no more than 150), neuromodeling is carried out using the example of 50 RF constituent entities, which are part of the Central, Northwestern, Southern, North Caucasus, Ural and Far Eastern federal districts, for 2020–2022.

The "output" variable is social well-being index. The "input" variables include the first, second, fourth and fifth factors. Due to the relatively small data set, neuromodels are trained on the entire set of observations. The configuration of the formed Bayesian ensemble of neuromodels is presented in *Table 6*.

Five neuromodels with either one or two hidden layers were included in the Bayesian ensemble; the number of neurons in the hidden layers varied in increments of 4.

Table 5. Assessment of the adequacy of the clustering procedure of RF constituent entities in Deductor Studio Lite 5.1

Indicator	2020	2021	2022
Maximum error	2.58E-0.3	7.91E-0.3	2.88E-0.3
Mean error	2.83E-0.4	6.83E-0.4	3.63E-0.4
Recognized (%)	100	100	100
Source: own elaboration.			

Table 6. Configuration of the Bayesian ensemble of neuromodels

Neuromodel	Number of hidden layers	Number of neurons		Activation function
		in the first hidden layer	in the second hidden layer	
First	1	4	-	Hypertangent
Second	1	8	-	
Third	1	12	-	
Fourth	2	8	8	
Fifth	2	8	12	
Source: own elaboration.				

Let us evaluate the adequacy of the formed Bayesian ensemble of neuromodels using both automatically determined and independently calculated indicators (*Tab. 7, 8*). In the second case, the mean (*E*) and maximum error (maxe) of initial data approximation are additionally determined, and the frequency criterion for the quality of neuromodeling is also calculated (the number (N) and percentage (P) of correctly recognized observations with 5 and 8% individual approximation error).

According to both the mean and maximum error, the fourth artificial neural network is the most adequate of the five neuromodels. The fifth neuromodel demonstrates similar values of indicators.

Based on the mean approximation error and the frequency quality criterion, the second neuromodel is the most adequate, while the fifth artificial neural network is the most adequate according to the maximum approximation error. Taking into account the values of all adequacy indicators, we can conclude that artificial intelligence allows approximating with a high degree of accuracy the initial data necessary to form a forecast for the social well-being index of the population of RF constituent entities.

We implement the predictive function using the formed Bayesian ensemble of neuromodels using the example of leader regions of the rating for 2024–2025. (*Tab. 9, Fig. 2*); the values of factor indicators were assigned by experts based on the trends of their change in dynamics for 2015–2022. According to the formed forecast, in 2024–2025, Moscow is expected to maintain its leadership in the social well-being index.

It is predicted that the value of the effective indicator in the leading region will remain practically the same. The Magadan Region and Saint Petersburg are expected to rank 2nd and 3rd, respectively; while an increase in the index value is expected for each of the two above-mentioned regions-leaders of the rating in 2024–2025.

Table 7. The system of automatically calculated indicators of the adequacy of the Bayesian ensemble of neuromodels

Neuromodel	Maximum error	Mean error	Recognized (%)
First	9.13E-0.3	1.23E-0.3	100
Second	9.17E-0.3	9.35E-0.4	100
Third	1.08E-0.2	1.23E-0.3	100
Fourth	5.32E-0.3	4.87E-0.4	100
Fifth	5.65E-0.3	5.17E-0.4	100
Source: own elaboration.			

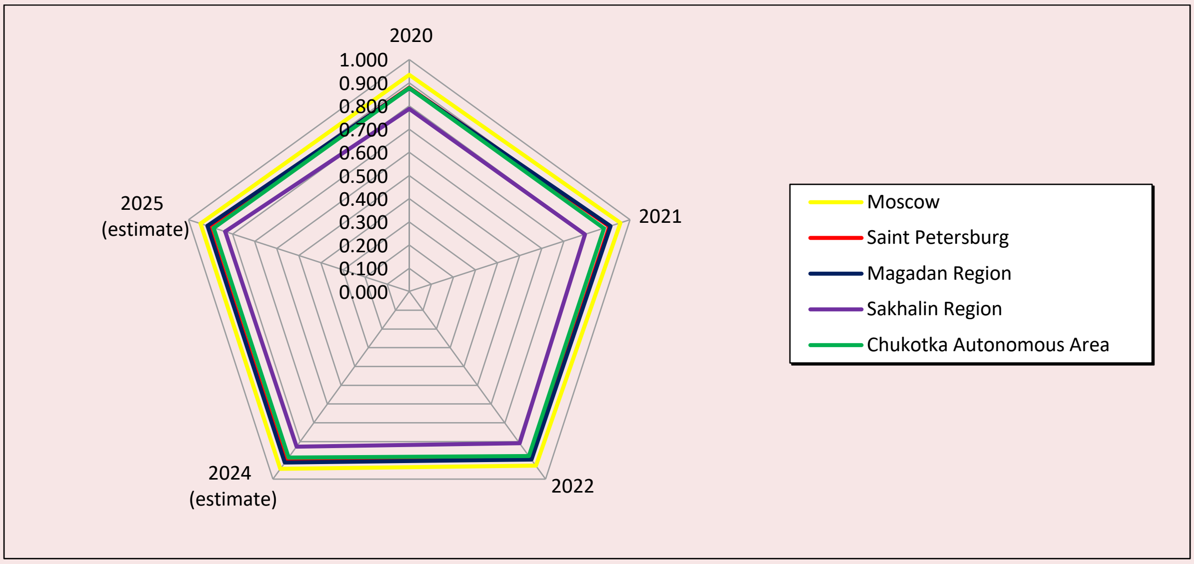
Table 8. Additional indicators of the adequacy of the Bayesian ensemble of neuromodels

Neuromodel	E, %	N		P		maxe, %
		e = 5%	e = 8%	e = 5%	e = 8%	
First	3.7	109	140	72.7	93.3	13.9
Second	2.8	127	143	84.7	95.3	14.4
Third	3.3	117	142	78	94.7	13.6
Fourth	3.9	104	135	69.3	90	11.3
Fifth	3.6	110	138	73.3	92	10.8
Source: own elaboration.						

Table 9. Forecasting the social well-being index (y) using artificial intelligence

RF constituent entity	2024 (estimate)					2025 (estimate)				
	x_1	x_2	x_4	x_5	y	x_1	x_2	x_4	x_5	y
Moscow	0.995	1.000	0.910	0.997	0.945	0.997	1.000	0.915	0.998	0.946
Saint Petersburg	0.905	0.810	0.905	1.000	0.905	0.910	0.820	0.910	1.000	0.908
Magadan Region	1.000	0.800	0.980	0.900	0.912	1.000	0.810	0.985	0.910	0.914
Sakhalin Region	1.000	0.625	0.890	0.935	0.827	1.000	0.635	0.910	0.940	0.834
Chukotka Autonomous Area	0.985	0.870	1.000	0.925	0.885	0.990	0.880	1.000	0.930	0.887
Source: own elaboration.										

Figure 2. Social well-being index of the population of the top regions in the rating



Source: own elaboration.

Based on the data in Figure 2, there is a high density of final results in 2020–2022 between the 2nd–4th leading regions of the rating according to the social well-being index. And it is expected to remain throughout the entire forecasting horizon. It is necessary to note a fairly large gap between the 5th and 4th places in the index rating.

Thus, the index method in combination with artificial intelligence ensures high accuracy of assessment of the social well-being index of the population of RF constituent entities. The results obtained in the course of the empirical study can be interpreted within the framework of the so-called ordinalist “increase – decrease” paradigm: (Fleming, 1952).

Currently, as a rule, authorized agencies make forecasts of socio-economic indicators at the meso-level using a scenario approach implemented by experts and therefore characterized by a high degree of subjectivity. The developed tools will improve the accuracy of the prospective assessment of the phenomenon in question.

Discussion of the results

Modern Russia, as noted in the works (Lapin et al., 2020; Chernysh, 2021; Pugachev, 2023), has a high (or even excessive) level of monetary inequality of the population compared with a number of countries around the world. An identical conclusion can be drawn independently if we analyze the change in the dynamics of the value of the Gini coefficient for per capita money income for Russia when compared with other countries.

We should note that in modern Russia (2000 – present), the "peak" in the Gini coefficient for money income (about 0.42–0.422 in 2007–2010 and 2012) has been passed. In 2022, the value of the indicator repeated the historical minimum recorded in 2000 (0.395). In addition, the situation in the context of regions differs significantly from the Russian average. Some of them have a significantly higher level of monetary inequality. So, in particular, the value of the Gini coefficient for money income in 2022 in Moscow was 0.412, in the Nenets Autonomous Area – 0.419, in the Tyumen Region – 0.426, in the Yamal-Nenets Autonomous Area – 0.44, in the Chukotka Autonomous Area – 0.41. At the other pole there are regions with monetary inequality significantly below the national average: the Kostroma Region, the Republic of Khakassia – 0.320, the Republic of Kalmykia – 0.313, the Republic of Ingushetia – 0.311, the Jewish Autonomous Region – 0.310. The coefficient of interregional differentiation (the ratio of the highest value of the indicator to the lowest) is 1.4 times.

In 2022, the highest purchasing power of the population by per capita money income was recorded in the Yamal-Nenets Autonomous Area (6.1 SM (subsistence minimums) reg.), Moscow (4.8 SM reg.), Saint Petersburg (4.6 SM reg.), the Nenets Autonomous Area (4.3 SM reg.), and the Sakhalin Region (4.0 SM reg.). At the opposite pole were the Jewish Autonomous Region (1.9 SM reg.), the Republic of Kalmykia (1.89 SM reg.), the Karachay-Cherkess Republic (1.8 SM reg.), the Republic of Ingushetia (1.7 SM reg.) and the Republic of Tyva (1.6 SM reg.). The coefficient of interregional differentiation of the purchasing power of the population (the ratio of the highest to the lowest values of the indicator) is 3.8 (Bobkov, Gulyugina, 2023, pp. 114, 137–139).

The coefficient of interregional differentiation of the social well-being index in 2022 amounted to 3.65 times, which is 0.96 of the value of a similar index of purchasing power of the population, i.e. they have close values. There are also points of intersection in the distribution of RF constituent entities at different poles of the rating. For example, in the group of leading regions for the two above-mentioned indicators are Moscow, Saint Petersburg and the Sakhalin Region, and in the group of outsider regions – the Karachay-Cherkess Republic and the Republic of Tyva.

We should note that the close coefficients of interregional differentiation according to the social well-being index and the purchasing power of the population are significantly higher than the similar coefficient measuring the interregional differentiation of the distribution of living standards resources (in our case, the Gini coefficient for money income), by about 2.6–2.7 times.

At the same time, the results of measuring interregional differentiation by the social well-being index partially do not coincide with the results of its measurement by the purchasing power of the population by per capita money income. As of 2022, the lists of leaders and outsiders in the social well-being index did not completely coincide: according to the first index, the upper group, besides three matching constituent entities, included the Yamal-Nenets Autonomous Area and the Nenets Autonomous Area; the lower group, besides three matching constituent entities, included the Jewish Autonomous Region, the Republic of Kalmykia and the Republic of Ingushetia; according to the second index, respectively, the Magadan Region, the Chukotka Autonomous Area, and the Altai Republic, the Chechen Republic, as well as the Kurgan Region.

This is due to the fact that the social well-being index takes into account a greater number of factors determining its value, despite the fact that the purchasing power of the population in terms of the average monthly accrued wages of employees of organizations is decisive in it.

For a more detailed analysis of the results of the study, including their predictive assessment, i.e. determining which factor indicators have led / may lead to an improvement or deterioration in the social well-being index, it is necessary to decompose the factors embedded in the model for determining this index, or use a parallel forecast of the purchasing power of the population, which is the factor indicator most strongly influencing the dynamics of the social well-being index.

Conclusion

Taking into account the vastness of Russia, diversity of its living conditions and a large number of regions, the study focused on exploring the possibilities for more accurately determining the social well-being of the population to improve the effectiveness of social policy at the meso-level of management and the use of the social well-being index to assess the interregional differentiation of living standards. Currently, the effectiveness of the activities of executive authorities in RF constituent entities is assessed on a regular basis (annually). In terms of living standards, it is based on taking into account changes in the dynamics of growth rates of real money incomes of the population and real average monthly wages. In interregional comparisons of living standards, they, in terms of official estimates, do not take into account regional differences in the purchasing power of the population and a number of other factors that shape the standard of living, in connection with which, as part of our study, an attempt was made to eliminate this disadvantage and propose our own approach consisting in determining the social well-being index using artificial intelligence, which more accurately measures the dynamics of the standard of living and can be used to assess its interregional differentiation.

Empirically, it has been proved that the index method in combination with artificial intelligence makes it possible to approximate regional statistics data with a higher degree of accuracy. Thus, for each of the three developed traditional econometric models the mean approximation error was about 9–10%, while any of the five artificial neural networks included in the Bayesian ensemble allowed approximating the initial data with a mean error of 3–4%. Therefore, the medium-term forecast of the social well-being of the population of RF constituent entities on the example of the leading regions of the rating was formed using the index method and artificial intelligence.

Thus, the results obtained in the framework of the study can:

– be a scientific basis for making effective management decisions by the leadership of Russian regions to improve living standards;

– be used by federal authorities to assess the interregional differentiation of living standards according to the social well-being index;

– orient the state social policy toward raising the social well-being index in Russian regions and equalizing its regional values.

We do not exclude the possibility of using all the methods discussed above to assess social dynamics in the regions of the Russian Federation and measure interregional differentiation: resource provision of living standards (Gini index by per capita money income); purchasing power of the population by per capita money income and the social well-being index. Comparing these indicators will make it possible to identify specific and multidirectional processes that affect the formation of the standard of living, and to make "balanced" management decisions. Accordingly, it would be useful to conduct interregional comparisons for all three indicators considered: the Gini index by income, the purchasing power of the population by per capita money income and the social well-being index.

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Information about the Authors

Vyacheslav N. Bobkov – Doctor of Sciences (Economics), director of the scientific center, Plekhanov Russian University of Economics (36, Stremyanny Lane, Moscow, 115054, Russian Federation); Chief Researcher, head of the scientific sector, Institute of Economics of the RAS (32, Nakhimovskiy Avenue, Moscow, 117218, Russian Federation; e-mail: bobkovvn@mail.ru)

Roman V. Gubarev – Candidate of Sciences (Economics), associate professor of department, Plekhanov Russian University of Economics (36, Stremyanny Lane, Moscow, 115054, Russian Federation; e-mail: gubarev.roma@yandex.ru)

Evgeny I. Dzuyba – Research Associate, Institute of Social and Economic Research of the UFRC of the RAS (71, Oktyabrya Avenue, Ufa, 450054, Russian Federation; e-mail: intellectRus@yandex.ru)

Fanil S. Fayzullin – Doctor of Sciences (Philosophy), Chief Researcher, Institute of social and Economic Research of the UFRC of the RAS (71, Oktyabrya Avenue, Ufa, 450054, Russian Federation; e-mail: fayzullin.f@gmail.com)

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