

# LIFE QUALITY AND HUMAN POTENTIAL OF TERRITORIES

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## EDUCATIONAL COMPONENT OF HUMAN CAPITAL: SPATIAL DIFFERENTIATION OF RUSSIAN REGIONS AND THE FORECAST SCENARIO (CASE STUDY OF THE REPUBLIC OF UDMURTIA)



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*The educational component of human capital is a key factor in sustainable regional development. However, the development of regional education policy and forecasting of its territorial potential are hampered by pronounced spatial heterogeneity and lack of consideration of the structural features of the educational component of the human capital of the constituent entities of the Russian Federation. The lack of methodological tools that make it possible to classify regions according to the structure of the educational component of human capital and predict the development of its types determines the aim of the study, which is to identify stable clusters of regions according to appropriate indicators to typify existing structural problems and build a medium-term forecast of the dynamics of the indicators under consideration for a typical representative of one of the clusters. The scientific novelty of the work consists in the application of clustering methods to typologize regions according to the educational*

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*component of human capital and predictive modeling of the development of a typical representative of a cluster. Clustering was performed using two methods: k-means and hierarchical (Ward's method), followed by checking the consistency of the results using the adjusted Rand index (ARI). The cluster analysis revealed five homogeneous groups of subjects of the Russian Federation with different structures of the educational component of human capital: the country's educational centers, regions with a predominance of higher, secondary vocational and general education, as well as regions with a shortage of vocational education. For a typical representative of the third cluster (Republic of Udmurtia), forecasts of six indicators up to 2030 have been made with high accuracy (the average relative error is  $\leq 5.3\%$ ). We have been established that the region is expected to increase the specialization of mid-level personnel training (an increase in the proportion of students in secondary vocational education institutions to 38.9%). For further research, it is proposed to include indicators characterizing the effectiveness of educational systems within the selected clusters, and to analyze the inter-cluster dynamics of the educational component of human capital to form differentiated recommendations for regional educational policy.*

*Human capital, educational component, regional clustering, forecasting, autoregressive models, Republic of Udmurtia.*

## **Introduction**

The rational use of resources, ensured by competent regional governance, makes it possible to achieve the goals and objectives of a territory's socio-economic development. One of the most important development resources is human capital (HC) (Mazelis et al., 2020; Frolov et al., 2025). In economic theory, human capital is understood as the body of knowledge, skills, competencies, and abilities of the population that can be used to produce goods and generate economic growth (Lutz, Butz, 2014). It is human capital, or more precisely its qualitative characteristics, that takes center stage, determining the innovative potential of regions.

Within the structure of human capital, the educational component occupies a special place. Education serves as the foundation for its formation, because it is through the education system that knowledge, skills, and competencies are transmitted, which in turn lead to higher labor productivity and economic growth. Researchers note that education is a key institution for the reproduction of human

capital, and investment in it yields long-term economic and social dividends (Leonidova, Golovchin, 2019). A high level of education among the population correlates with higher innovation activity and greater economic adaptability to technological change (Supaeva et al., 2024). Quality education expands opportunities for personal fulfilment, helps build civil society, and reduces social tension (Napso, 2022).

Studying the educational component of human capital is arguably the most significant factor in the socio-economic development of territories (Baranova, 2022; Danova, Sira, 2023). The effects of accumulating the educational component of human capital are seen not only in improved macroeconomic indicators but also in a better quality of life for the population, making it a priority area for regional policy.

There are several approaches to measuring the educational component of human capital. According to Chinese researchers, the evolution of measurement methods has moved from simple indicators (years of schooling) to

complex composite indicators that account for education quality (Tang et al., 2025). In global practice<sup>1</sup>, certain approaches to measuring the educational component of human capital have been established, using the following types of indicators:

1) stock indicators, which measure the accumulated educational potential of the population: average years of schooling, distribution of the population by education level, etc.;

2) flow indicators, which reflect current investments in human capital and the scale of training: enrollment rates, number of students and teachers per capita, etc. (these indicators form the information base of this study, as they allow for an assessment of the current reproduction of human capital across regions);

3) quality indicators, which capture learning outcomes: cognitive skills, literacy, results of comparative assessments;

4) composite indicators, which combine various aspects of the educational component of human capital (e.g., the World Bank's Human Capital Index<sup>2</sup> includes an education component measured as the product of expected years of schooling and standardized test scores).

Given the significant spatial heterogeneity of the Russian Federation – characterized by differences in socio-economic development, demographic structure, and historically established regional specializations – a differentiated approach to analyzing the educational component of human capital is necessary. Averaging indicators at the national level conceals substantial interregional disparities and makes it impossible to formulate effective policy decisions. Therefore, research that not only assesses the current state of the

educational component of human capital but also predicts its dynamics while accounting for regional specificities is highly relevant.

When studying spatial differentiation, it is important to identify broad, relatively homogeneous groups of regions – clusters. This approach is widely used by both Russian and international researchers to overcome the limitations of aggregate regional analysis (Dobrokhleb, Kondakova, 2022; Korir, 2024). Clustering makes it possible to pinpoint problem areas and subsequently design targeted policies to enhance regional human capital (Murgante et al., 2025). Despite the widespread use of clustering methods in regional analysis (Leonidova et al., 2022; Ketova et al., 2021), approaches specifically focused on the educational component of human capital remain significantly limited. Existing studies tend to focus either on integral assessments of the socio-economic situation of regions, where education is only one of many factors, or on analyzing isolated statistical indicators without identifying stable structural relationships among them. This approach fails to fully account for the inertial nature of educational systems and their role in shaping long-term development trajectories of territories.

Beyond territorial analysis, it is also necessary to assess the situation within homogeneous groups and to build scientifically grounded forecasts of human capital dynamics (Jagodka, 2025). Regression and autoregressive models (Vavilova, 2023), as well as various machine learning methods – including clustering algorithms – remain the most widely used tools in econometric modelling, often applied to simulate complex, structured processes (Kitova et al., 2020). This suggests the promise of a hybrid

<sup>1</sup> Mind the Learning Gap: A Methodological Look into World Bank's New Human Capital Index. NORRAG. 2018. Available at: <https://www.norrageducation.org/mind-the-learning-gap-a-methodological-look-into-world-banks-new-human-capital-index-by-ji-liu/> (accessed: 10.03.2026).

<sup>2</sup> Human Capital Project. World Bank Group. Available at: <https://www.worldbank.org/en/publication/human-capital> (accessed: 10.03.2026).

approach that leverages the strengths of different methods: machine learning effectively identifies stable clusters, while econometrics enables reliable forecasting. Despite the existence of these well-developed strands of research, no studies have yet used clustering of regions based specifically on the educational component of human capital as a basis for regional typology and for constructing predictive models of human capital development within specific clusters.

The specificity of the educational component of human capital lies in the fact that it not only reflects the current state of a region but also shapes its future potential. Moreover, Russia's high spatial differentiation manifests itself not only in quantitative differences (e.g., the share of students) but also in structural ones – namely, the balance between different levels of education (general, vocational secondary, and higher education). Existing typologies often ignore this heterogeneity, grouping regions with fundamentally different educational strategies together based on general socio-economic development levels. Thus, the task of identifying homogeneous groups of regions according to the educational component of human capital – and assessing the stability of this structure over time – remains unresolved.

The statement of the scientific problem stems from the contradiction between the need to account for the structural features of the educational component of human capital when designing regional policy, and the lack of methodological tools that would not only classify regions according to this characteristic but also predict the development of the identified types. This leads to the formulation of the following scientific hypotheses.

1. Hypothesis of structural heterogeneity: the constituent entities of the Russian Federation form stable typological groups that differ not so much in scale as in the structure of the educational component of human capital

(i.e., the balance between different levels of education and training).

2. Hypothesis of inertia: the identified types of regions exhibit a high degree of stability over time, and the dynamics of indicators within a cluster follow common patterns, making it possible to construct forecasts for a typical representative of that cluster.

The aim of the study is to identify stable clusters of regions based on indicators of the educational component of human capital, in order to typify existing structural problems and to construct a medium-term forecast of the dynamics of the selected indicators for a typical representative of one of the resulting clusters – an average Russian region (Udmurt Republic).

The methodological framework of the study comprises modern methods of applied statistics, multivariate data analysis, and econometrics, including clustering techniques, regression analysis, and predictive modelling. The practical significance of the work lies in creating a tool for typologizing regions and forecasting the development of the educational component of human capital in the regions of the Russian Federation. The results can be used by governing bodies for evidence-based planning and the design of differentiated socio-economic development policies.

### **Materials and methods**

There is a fairly wide set of indicators that characterize the educational component of human capital. We propose to consider six key per-capita indicators, presented in *Table 1*. They can be described as indicators of the development of the education sector in a region (the share of students, teachers, etc.). At the same time, they reflect the current flow of educational services and serve as proxy variables for investment in human capital. The indicators (X1–X6) make it possible to assess both the scale

**Table 1. Indicators used to analyze the educational component of human capital**

No.	Indicator code	Indicator name	Explanation of calculation
1	X1	Share of school teachers in the population, ‰	Ratio of the number of teachers in organizations providing educational programs for primary, basic, and secondary general education to the total population
2	X2	Share of teachers in secondary vocational institutions in the population, ‰	Ratio of the number of teachers delivering educational programs for secondary vocational education to the total population
3	X3	Share of university teaching staff in the population, ‰	Ratio of the number of academic staff in organizations providing educational programs for bachelor's, specialist, and master's degrees to the total population
4	X4	Share of school students in the population, ‰	Ratio of the number of students enrolled in educational programs for primary, basic, and secondary general education to the total population
5	X5	Share of students in secondary vocational institutions in the population, ‰	Ratio of the number of students enrolled in secondary vocational education programs to the total population
6	X6	Share of university students in the population, ‰	Ratio of the number of students enrolled in bachelor's, specialist, and master's degree programs to the total population
Source: own compilation.			

and the structure of current education and training across regions. All indicators are standardized by the population size of the region and expressed in per mille (‰), which ensures their comparability across regions with different demographic situations.

However, the assessment of the educational component of human capital is not exhausted by the indicators presented (qualitative characteristics, results of independent assessments, data on additional education and retraining are also important). The study is limited by the availability and comparability of official statistics at the regional level. As the information base expands (for example, with the emergence of regular data on education quality assessment results across Russian regions), the

set of indicators may be supplemented.

The study uses panel data provided by the Federal State Statistics Service of the Russian Federation (Rosstat)<sup>5</sup> and the Ministry of Education of Russia<sup>4</sup> for the period 2000–2023, disaggregated by constituent entity of the Russian Federation. To describe, summarize, and visualize the available information, descriptive statistics were calculated (Vorokova, Sennikova, 2021): mean, median, mode, range, variance, standard deviation, skewness, and kurtosis.

Next, clustering was performed, which involves partitioning the set of Russian regions under study into groups (clusters) that are homogeneous with respect to the indicators of the educational component of human capital.

<sup>5</sup> Regions of Russia. Basic characteristics of the constituent entities of the Russian Federation. Federal State Statistics Service. Available at: <https://rosstat.gov.ru/folder/210/document/13205> (accessed: 25.09.2025).

<sup>4</sup> Information on students in grades 1–12. Ministry of Education of the Russian Federation. Available at: [https://edu.gov.ru/activity/statistics/actual\\_statistical\\_information](https://edu.gov.ru/activity/statistics/actual_statistical_information) (accessed: 25.10.2025).

Various clustering algorithms exist (Shamray-Kurbatova et al., 2021; da Silva, Soares, 2025), and their results are highly consistent when analyzing data of a similar nature. This study applies Ward's method of hierarchical clustering (Mouronte-Lopez, Savall, 2024), in which, at each step, the two clusters whose merger leads to the smallest increase in total within-cluster variance (the sum of squared Euclidean distances from points to their cluster centroid) are combined. The output of the hierarchical algorithm is a tree-like structure (dendrogram).

The stability and statistical significance of the cluster solution are tested using an empirical rule: a stable grouping should persist when clustering methods are changed. The assumption of stability is accepted if the proportion of agreement between clustering results exceeds 70%. In addition to this approach, the Adjusted Rand Index (ARI) is also used (Dubravskaya, 2020; Struzhko et al., 2018).

Modelling and forecasting of the educational component indicators for one of the constituent entities of the Russian Federation is carried out using an autoregressive model based on annual data of the human capital educational component indicators for the period 2000–2023. The model form is ARIMA (p, d, q), where p is the autoregressive order, q is the moving average order, and d is the order of differencing required to achieve a stationary series. The use of the ARIMA (p, d, q) model is motivated by the non-stationarity of time series, which is characteristic of most socio-economic indicators (Zou, 2024; Sinu et al., 2024). The best model specification is selected by minimizing the corrected Akaike Information Criterion (AICc).

Forecast quality is evaluated using two metrics: RMSE (root mean square error) and MAPE (mean absolute percentage error):

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}, \quad (1)$$

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \cdot 100\%, \quad (2)$$

where  $n$  is the number of observations,  $y_i$  is the actual value, and  $\hat{y}_i$  is the predicted value. These metrics are widely used to assess the accuracy of predictive models in socio-economic research (Yan, 2024).

The analysis of the initial statistical dataset, subsequent clustering, modelling, and forecasting are carried out in the RStudio development environment using the R programming language. For visualization of the territorial distribution of the educational component of human capital across Russia and the clustering results, the Yandex.Maps JavaScript API web map was used.

## Results

During the study, descriptive statistics were calculated for the indicators of the educational component of human capital across the constituent entities of the Russian Federation. The results are presented in *Table 2*.

A significant differentiation in the values of all indicators of the educational component of human capital across the constituent entities of the Russian Federation is observed. This is confirmed by the large range, which is particularly pronounced for the share of university students (X6: 70.7‰), the share of school students (X4: 124.8‰), and the share of students in secondary vocational education (SVE) programs (X5: 27.5‰). High coefficients of variation indicate substantial differences in the development of the education sector between regions. The greatest differences are observed in the higher education system, as the corresponding indicators (X3 and X6) have the highest coefficients of variation (0.6 and

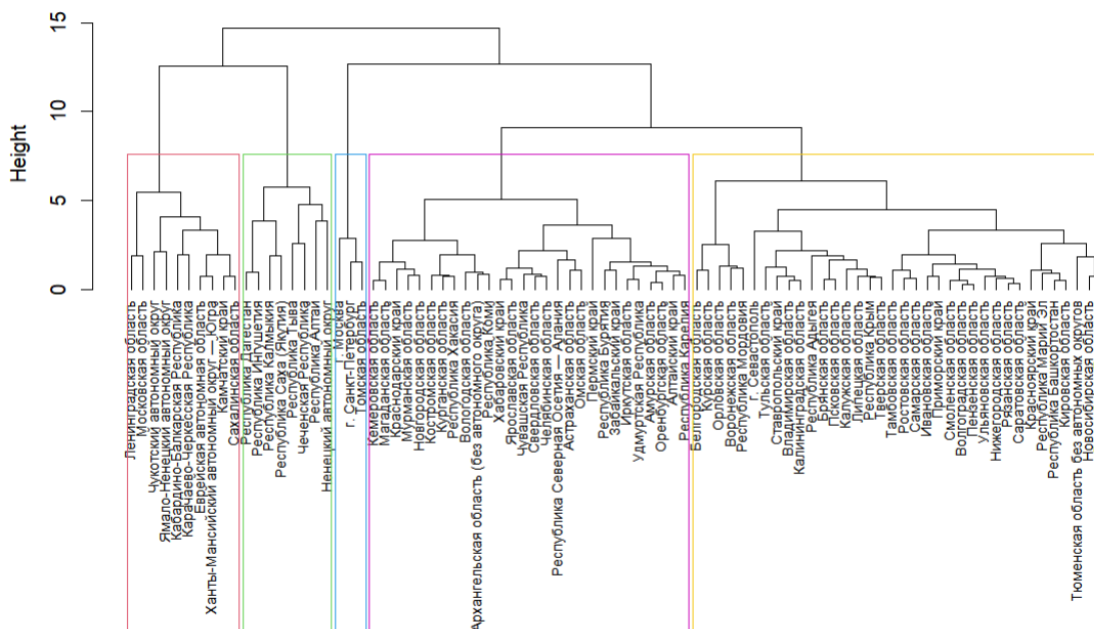
0.5, respectively). The skewness coefficients for the share of teachers (X1), university teaching staff (X3), school students (X4), and university students (X6) are positive. This means that in most regions, the values of these indicators are below the average, with higher values concentrated in a minority of regions.

Based on a visual analysis of the dendrogram obtained using Ward’s method, it was decided to distinguish five clusters (Fig. 1). To test the stability of the obtained solution, the k-means method was also applied: the groupings of regions using the two methods coincide by 93%, which exceeds the empirical threshold

**Table 2. Descriptive statistics of educational component indicators of human capital by constituent entities of the Russian Federation, 2023, ‰**

Characteristic	X1	X2	X3	X4	X5	X6
Minimum	4.8	0.3	0.0	91.3	11.1	0.0
Maximum	16.0	1.7	3.7	216.1	38.6	70.7
Range	11.2	1.4	3.7	124.8	27.5	70.7
Arithmetic mean	8.2	1.0	1.2	129.0	26.4	24.1
Median	7.6	1.0	1.1	126.3	26.6	23.0
Mode	7.5	1.0	–	–	23.9	–
Corrected variance	4.7	0.0	0.4	428.5	17.2	131.5
Standard deviation	2.2	0.2	0.6	20.7	4.1	11.5
Coefficient of variation	0.3	0.2	0.6	0.2	0.2	0.5
Skewness	1.8	-0.2	1.7	1.5	-0.8	1.2
Kurtosis	6.7	4.7	8.4	7.1	5.1	7.0

Source: own compilation.



**Figure 1. Dendrogram of hierarchical clustering of the constituent entities of the Russian Federation by indicators of the educational component of human capital, 2023**

Source: own compilation.

of 70%, confirming the stability and statistical significance of the five identified clusters. The Adjusted Rand Index (ARI) was 0.782, also demonstrating strong agreement. Thus, regions consistently group into the same types regardless of the algorithm used.

The results of clustering based on the indicators of the educational component of human capital are presented in *Table 3*.

The characteristics of the five typologically homogeneous groups of constituent entities of the Russian Federation are presented in *Table 4*.

**Cluster 1 “Higher Education Leaders”.** The first cluster includes Moscow, Saint Petersburg, and the Tomsk Region. This group is characterized by high values of indicators related to higher education. The share of university students (X6 = 64.1‰) in this cluster is 2.6 times higher than the national average (24.1‰). The share of university teaching staff (X3 = 3.6‰) in these regions is also the highest, exceeding the national average (1.2‰) by a factor of three. This identifies these regions as unique educational hubs that function as centers for the reproduction and attraction of

**Table 3. Clusters of constituent entities of the Russian Federation by indicators of the educational component of human capital, 2023**

Cluster	Constituent entities of the Russian Federation
1	Moscow, Saint Petersburg, Tomsk Region
2	Republic of Adygea, Republic of Bashkortostan, Belgorod Region, Bryansk Region, Vladimir Region, Volgograd Region, Voronezh Region, Ivanovo Region, Kaliningrad Region, Kaluga Region, Kirov Region, Krasnoyarsk Territory, Republic of Crimea, Kursk Region, Lipetsk Region, Republic of Mari El, Republic of Mordovia, Nizhny Novgorod Region, Novosibirsk Region, Oryol Region, Penza Region, Primorye Territory, Pskov Region, Rostov Region, Ryazan Region, Samara Region, Saratov Region, Sevastopol, Smolensk Region, Stavropol Territory, Tambov Region, Republic of Tatarstan, Tver Region, Tula Region, Tyumen Region (without autonomous areas), Ulyanovsk Region
3	Altai Territory, Amur Region, Arkhangelsk Region (without autonomous area), Astrakhan Region, Republic of Buryatia, Vologda Region, Trans-Baikal Territory, Irkutsk Region, Republic of Karelia, Kemerovo Region, Komi Republic, Kostroma Region, Krasnodar Territory, Kurgan Region, Magadan Region, Murmansk Region, Novgorod Region, Omsk Region, Orenburg Region, Perm Territory, Sverdlovsk Region, Republic of North Ossetia – Alania, Udmurt Republic, Khabarovsk Territory, Republic of Khakassia, Chelyabinsk Region, Chuvash Republic, Yaroslavl Region
4	Republic of Altai, Republic of Dagestan, Republic of Ingushetia, Republic of Kalmykia, Nenets Autonomous Area, Republic of Sakha (Yakutia), Republic of Tyva, Chechen Republic
5	Jewish Autonomous Region, Kabardino Balkarian Republic, Kamchatka Territory, Karachay Cherkess Republic, Leningrad Region, Moscow Region, Sakhalin Region, Khanty Mansi Autonomous Area – Yugra, Chukotka Autonomous Area, Yamal-Nenets Autonomous Area

Source: own compilation.

**Table 4. Average values of educational component indicators in clusters of constituent entities of the Russian Federation, 2023**

Cluster	Number of regions in the cluster	Average value of indicator in the cluster, ‰					
		X2	X3	X4	X5	X6	
1	3	6.4	0.9	3.6	107.1	22.7	64.1
2	36	7.2	1.0	1.3	116.8	25.3	27.0
3	28	8.0	1.1	1.1	133.9	29.9	22.7
4	8	13.6	1.1	0.8	169.1	28.1	18.0
5	10	8.3	0.6	0.5	133.7	20.1	10.4
Average for Russia		8.2	1.0	1.2	129.0	26.4	24.1

Source: own compilation.

human capital in the sphere of higher education for the entire country.

**Cluster 2 “Regions with an Emphasis on Higher Education (HE)”.** This cluster includes 36 constituent entities of the Russian Federation. The key feature of this cluster is the high share of university teaching staff ( $X3 = 1.3\%$ ), which exceeds the national average, combined with the second-highest share of university students ( $X6 = 27.0\%$ ). This indicates not only a high demand for higher education but also a comparable development of the human resources needed to deliver it. Thus, the regions in the second cluster act as local hubs for attracting students to higher education.

**Cluster 3 “Regions with an Emphasis on Secondary Vocational Education (SVE)”.** This cluster comprises 28 constituent entities of the Russian Federation, including the Udmurt Republic. The profile of the third cluster is shaped around secondary vocational education. Regions in this group have the highest share of SVE students among all clusters ( $X5 = 29.9\%$ ). They also have a high share of school students ( $X4 = 133.9\%$ ), exceeding the national average. Higher education indicators ( $X3, X6$ ) are somewhat below the national average. This cluster consists of regions whose educational strategy focuses on providing the economy with mid-level professionals.

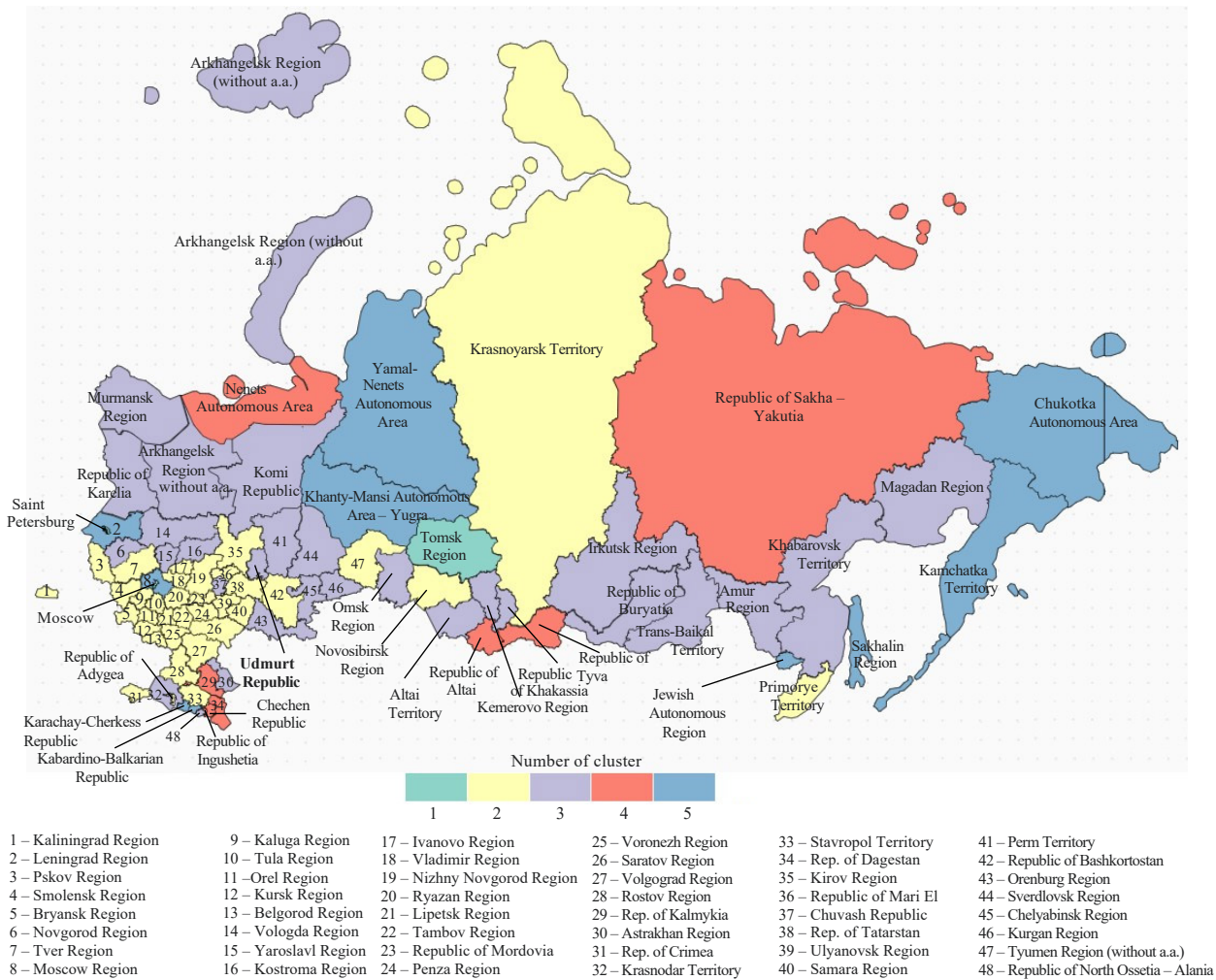
**Cluster 4 “Regions with a High Share of General Education”.** This cluster includes eight constituent entities. This group is characterized by a pronounced demographic specificity, reflected in the highest values among all clusters for the share of teachers ( $X1 = 13.6\%$ ) and the share of school students ( $X4 = 169.1\%$ ). At the same time, the indicators for SVE and HE are at or below the national average. This points to a structural imbalance: the educational systems of these regions experience an increased burden at the general education level while

the development of subsequent educational pathways is relatively insufficient.

**Cluster 5 “Regions with a Deficit of Vocational Education”.** This cluster includes 10 constituent entities. It unites regions that have recorded the lowest values for indicators related to vocational training ( $X2, X3, X5, X6$ ). At the same time, general education parameters ( $X1, X4$ ) are close to the national average. This profile indicates a systemic weakness in the SVE and HE sectors, which creates constraints on the formation of regional human capital and may stimulate the out-migration of young people to regions with more developed educational infrastructure.

Figure 2 visualizes the results of clustering the constituent entities of the Russian Federation according to the indicators of the educational component of human capital.

The absence in the typology of a cluster with a balanced ratio of all levels of education (general, SVE, HE) is, in our view, due to several reasons arising from the actual regional differentiation of the Russian Federation. First, the term “balance” implies the existence of some optimal ratio of indicators. However, in the analysis, clusters are formed based on actually observed statistical structures, not on normative ideas about what the structure should be. The k-means and Ward methods objectively group regions according to the actual proximity of indicators; we believe that if balanced regions existed as a stable group, they would have formed a separate cluster. Second, the results obtained indicate that in contemporary Russia, specialization of regions in specific educational levels is the rule, whereas balance is the exception. Empirically, groups with pronounced specialization emerged. Consequently, the institutional structure of educational systems in regions has historically developed under the influence of economic specialization, demographic factors,



**Figure 2. Visualization of the clustering results of the constituent entities of the Russian Federation by indicators of the educational component of human capital, 2023**

Source: own compilation.

and migration flows, which has led to shifts in one direction or another (i.e., belonging to a particular cluster).

The next stage of the research is to forecast the indicators of the educational component of human capital for a representative of a typical cluster. The Udmurt Republic (UR) was chosen as the object for predictive modelling for several reasons. First, the third cluster is one of the largest (28 constituent entities) and represents an “average cross-section” of the Russian economy. The values of the indicators (X1–X6) in the UR are very close to the centroid of the third cluster, allowing this region to be considered a typical

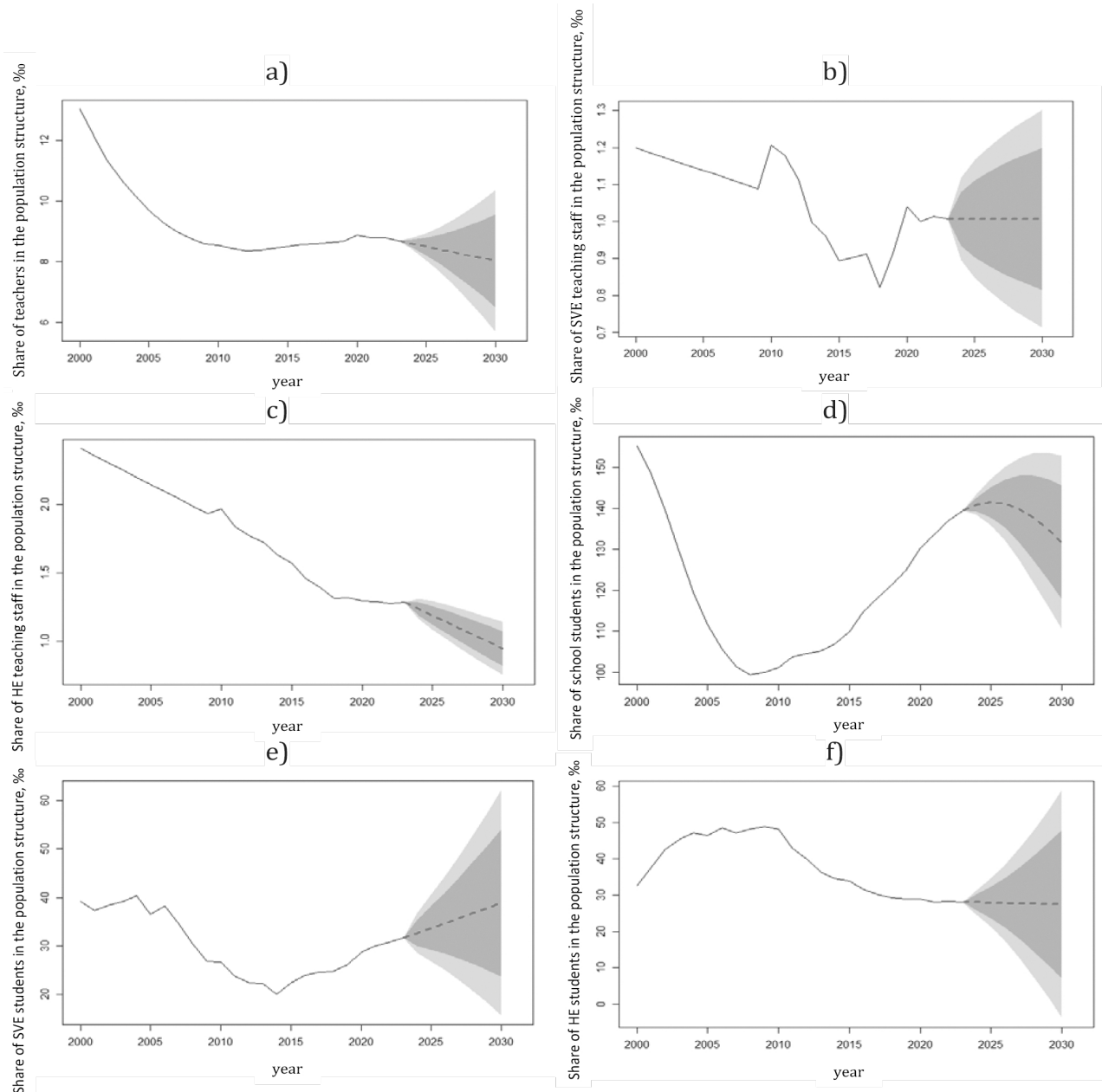
representative of the cluster. Second, the region’s economy has a pronounced industrial specialization (defense-industrial complex, mechanical engineering), making the study of the dynamics of the educational component (especially the SVE level) particularly relevant for understanding the staffing of priority industries. Choosing a typical representative makes it possible to extrapolate the identified patterns to the entire group with a certain degree of statistical reliability.

For each of the six indicators of the educational component of human capital in the UR, the best specification of an autoregressive model was selected based on minimizing

the corrected Akaike Information Criterion (AICc). Using the selected ARIMA model specifications, forecasts of the dynamics of the educational component indicators for the UR were constructed up to 2030. Visualization of the obtained trajectories, along with 80% and 95% confidence intervals, is presented in *Figure 3*. The MAPE values for the models do not exceed 5.3%, indicating their predictive

ability and the validity of using them to construct a medium-term forecast.

Analysis of the forecast values reveals trends in the development of the region's education sector. Of greatest interest is the dynamics of training indicators for secondary vocational and higher education, since these largely determine the Udmurt Republic's belonging to the third cluster. In the UR, a steady increase in the share



**Figure 3. Forecast of the educational component indicators of human capital for the Udmurt Republic up to 2030**

Note: a) share of teachers; b) share of SVE teaching staff; c) share of HE teaching staff; d) share of school students; e) share of SVE students; f) share of HE students

Source: own compilation.

of SVE students is expected, reaching 38.9‰ by 2030 (an increase of 6.2‰ compared to 2024). At the same time, the share of university students will slowly decline from 28.0‰ to 27.5‰ over the same period. This trend indicates a strengthening of the region's specialization in training mid-level professionals and, consequently, a consolidation of its position in the cluster with an emphasis on SVE. The forecast confirms that the UR's typological belonging to the third cluster will persist and deepen in the medium term.

The projected increase in the share of SVE students occurs against a background of low unemployment. According to data from early 2026, the actual unemployment rate in the UR is 0.3%, more than seven times lower than the national average (2.2%)<sup>5</sup>. At the same time, enterprises in the region face an acute labor shortage, with the number of open vacancies reaching 12,000<sup>6</sup>. The most sought-after specialists are in engineering and technical fields, as well as skilled trades: drivers, mechanics, electricians, lathe operators, and machine operators. Under these conditions, the projected increase in mid-level professional training is an adequate response to the current needs of the regional economy.

The decline in the share of HE students forecast for the period up to 2030 is largely due to demographic factors: over the past five years, the region's permanent population has decreased by 38,000 people, and as of early 2026 stood at 1.427 million<sup>7</sup>. Consequently, the observed trend may reflect not only the region's structural specialization but also the out-migration of young people to larger educational centers.

## Conclusions

The conducted study of spatial differentiation of the educational component of human capital in the regions of Russia has yielded a number of significant results. The application of a hybrid approach combining cluster analysis and econometric modelling made it possible not only to identify stable typological groups of regions but also to assess the development prospects of educational systems within the identified clusters.

The methodological significance of the work lies in substantiating the effectiveness of applying autoregressive models for medium-term forecasting of educational component indicators of human capital. The ARIMA models constructed for the Udmurt Republic as a typical representative of the third cluster demonstrated high forecast accuracy (the average relative error MAPE does not exceed 5.3%). Using the corrected Akaike Information Criterion in model specification made it possible to account for the limited length of the time series and avoid over-parameterization, which is particularly important when working with small-sample regional statistical data.

The hypotheses formulated in the introduction have been confirmed. The hypothesis of structural heterogeneity is confirmed by the identification of five stable clusters that differ not in scale but in the very structure of the educational component of human capital (i.e., the balance between different levels of education and training). The high Adjusted Rand Index (ARI = 0.782) and the 93% agreement between the results of two different clustering methods (hierarchical and k-means) statistically prove that Russian regions objectively group into types with unique educational profiles – from educational hubs

<sup>5</sup> Actual unemployment rate in Udmurtia amounted to 0.3%. Komsomolskaya Pravda. Izhevsk. 2026. January 12. Available at: <https://www.izh.kp.ru/online/news/6760524/> (accessed: 10.03.2026).

<sup>6</sup> 12,000 vacancies open at Udmurtia's factories. Gorod Glazov. 2026. January 20. Available at: <https://gorodglazov.com/news/37981> (accessed: 10.03.2026).

<sup>7</sup> Steps toward a decent life: How is the economy recovering? Federation of Trade Unions of the Udmurt Republic. Available at: <https://www.fpur.ru/news/ehkonomika/2026-01-19-2885> (accessed: 10.03.2026).

(Cluster 1) to regions with a deficit of vocational education (Cluster 5). The hypothesis of inertia has also been confirmed. First, the ability to construct accurate forecasts for a typical cluster representative (the Udmurt Republic) using ARIMA models ( $MAPE \leq 5.3\%$ ) indicates the presence of stable temporal patterns within the group. Second, the forecast up to 2030 shows a strengthening of the region's specialization, pointing to the preservation and deepening of its typological belonging to the SVE-oriented cluster.

It can be stated not only that the Udmurt Republic's specialization in training mid-level professionals persists, but also that this trend can be interpreted as an adaptation of the regional educational system to the structural features of the economy and the current labor market situation. Against the backdrop of record-low unemployment (0.3%) and an acute shortage of skilled workers (12,000 vacancies), the projected growth in the SVE student cohort to 38.9% by 2030 represents a response to the labor needs of enterprises in the defense-industrial complex and mechanical engineering. At the same time, maintaining this development trajectory requires complementary measures to improve the quality of life and wage levels in the region in order to retain trained specialists – a necessary condition for the realization of accumulated human capital.

The obtained results allow us to formulate a number of recommendations for regional policy. First, for regions of the third cluster (SVE-oriented), of which the Udmurt Republic is a typical representative, the strategic task is not simply to increase the share of SVE students, but to align the training structure with the current and prospective demand of the regional economy. Given the acute labor shortages, for example in the industry of the UR, it is recommended to strengthen targeted enrolment and deepen cooperation between colleges and

city-forming enterprises (defense-industrial complex, mechanical engineering) to adjust curricula to production needs.

Second, for regions of the fourth cluster (with a high share of school students and teachers), the priority should be not so much increasing the number of schools as optimizing the existing infrastructure and investing in the quality of education to ensure that school graduates successfully transition to the next levels of education. This implies developing career guidance programs and creating specialized classes (engineering, medical, etc.) on the basis of existing schools, which would help compensate for the structural imbalance without extensive network growth.

Third, for regions of the fifth cluster (with a deficit of vocational education), measures for the accelerated development of SVE and HE institutions are needed. This could be implemented through the creation of branches of sought-after universities and colleges, the development of educational voucher systems for applicants, and the introduction of regional allowances for vocational teaching staff. Such measures would make these territories more attractive to young people and help prevent out-migration.

Further research prospects include incorporating indicators that characterize the performance of educational systems (education quality, alignment of training structures with regional labor market needs, graduate migration flows, etc.). Analyzing the inter-cluster dynamics of the educational component of human capital also appears to be a relevant task. Solving this task would create a scientific basis for formulating differentiated recommendations to improve regional educational policy, aimed at overcoming existing imbalances and enhancing the contribution of educational potential to sustainable socio-economic development of territories.

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**Вавилова Д.Д., Бархатова Е.В.**

## **ОБРАЗОВАТЕЛЬНАЯ СОСТАВЛЯЮЩАЯ ЧЕЛОВЕЧЕСКОГО КАПИТАЛА: ПРОСТРАНСТВЕННАЯ ДИФФЕРЕНЦИАЦИЯ РЕГИОНОВ РОССИИ И ПРОГНОЗНЫЙ СЦЕНАРИЙ (КЕЙС УДМУРТСКОЙ РЕСПУБЛИКИ)**

*Образовательная составляющая человеческого капитала выступает ключевым фактором устойчивого регионального развития. Однако разработка региональной политики в области*

образования и прогнозирование его территориального потенциала затрудняются выраженной пространственной неоднородностью и отсутствием учета структурных особенностей образовательной составляющей человеческого капитала субъектов Российской Федерации. Отсутствие методического инструментария, позволяющего классифицировать регионы по структуре образовательной составляющей человеческого капитала и прогнозировать развитие его типов, определяет цель исследования, которая заключается в выявлении устойчивых кластеров регионов по соответствующим показателям для типизации имеющихся структурных проблем и построения среднесрочного прогноза динамики рассматриваемых показателей для типичного представителя одного из кластеров. Научная новизна работы состоит в применении методов кластеризации для типологизации регионов по образовательной составляющей человеческого капитала и прогнозного моделирования развития типичного представителя кластера. Кластеризация проведена с помощью двух методов: *k*-средних и иерархического (метод Уорда) с последующей проверкой согласованности результатов с использованием скорректированного индекса Рэнда (ARI). В ходе кластерного анализа выявлено пять гомогенных групп субъектов Российской Федерации с разной структурой образовательной составляющей человеческого капитала: образовательные центры страны, регионы с преобладанием высшего, среднего профессионального и общего образования, а также регионы с дефицитом профессионального образования. Для типичного представителя третьего кластера (Удмуртская Республика) построены прогнозы шести показателей до 2030 года с высокой точностью (средняя относительная ошибка  $\leq 5,3\%$ ). Установлено, что в регионе ожидается усиление специализации подготовки кадров среднего звена (рост доли обучающихся в организациях среднего профессионального образования до 38,9%). Для дальнейших исследований предлагается включить показатели, характеризующие результативность образовательных систем в рамках выделенных кластеров, и провести анализ межкластерной динамики образовательной составляющей человеческого капитала с целью формирования дифференцированных рекомендаций для региональной образовательной политики.

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