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Indicators of Population Welfare and Life Expectancy for the Arkhangelsk Oblast and Several Other Regions: Analysis and Modelling

Vladimir S. Stepanov^{1✉}, Cand. Sci. (Phys. and Math.), Leading Researcher

¹ Central Economics and Mathematics Institute of the RAS, Nakhimovskiy pr., 47, Moscow, Russia

¹ vladstep0355@gmail.com ✉, ORCID: <https://orcid.org/0000-0002-4478-376X>

Abstract. The article uses two regression models, previously constructed using panel data from the Central Federal District (CFD) and the Volga Federal District (VFD). The main focus of their application is on the Arkhangelsk Oblast. At the preliminary stage, two composite indicators were developed using principal component analysis combined with correlation analysis of the variables: the level of welfare and the development of transport infrastructure. They were calculated for each region using statistics from the CFD covering a number of years prior to the COVID-19 pandemic. In the next stage, two regression models with variable structures were constructed. The dependent variable in Model 1 is the indicator of the population's welfare, in Model 2 —the life expectancy at birth (LEB). Both of these models are new; the specification of Model 1 is provided for the Pomorye region. Another novel aspect is the formalization of the relationship between the aggregate welfare measure and indicators of infrastructure, the digitalization of the economy and life expectancy at birth. The models enabled the identification of informative factor variables, which were then examined in detail. Finally, they were applied to two regions of the Arctic Zone of the Russian Federation (AZRF) and a number of others. The factors in Model 1 that significantly influence the level of welfare were examined more closely: the infrastructure variable, digital economy indicators, life expectancy at birth, and others. Model 2, which functions well for many regions of the Russian Federation, is briefly described. Following a comparison of indicators for the Arkhangelsk Oblast and other regions, an illustrative example of forecasting for 2019 and 2020 is presented. The discussion identifies the region's problem areas and provides a brief overview of work on infrastructure, digitalization, innovations, and LEB. A number of parallels identified in regional development may also be of interest. Similarly, the research methodology can be applied to other territories of the AZRF and neighboring areas, as well as to other regions. The findings of the study may be useful to the authorities responsible for managing the regional development of territories within the AZRF or a number of other regions.

Keywords: regression model with variable structure, welfare level, transport infrastructure, digital economy, life expectancy, household income, innovation

Introduction

In accordance with a decree of the President of the Russian Federation¹, improving the quality of life and increasing the life expectancy of the population (in particular, life expectancy at birth) were identified as the most important priorities for the country and its regions. National

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¹ Decree of the President of the Russian Federation No. 1351 dated October 9, 2007, “On Approval of the Concept of Demographic Policy of the Russian Federation until 2025” (as amended and supplemented on July 1, 2014). URL: <https://base.garant.ru/191961/> (accessed 17 July 2025).

project “Demography”² is being implemented to address demographic challenges in the Arkhangelsk Oblast. A brief overview of studies analyzing and assessing the demographic situation in the regions is provided in the article (Kuznetsova, Vasilyeva, 2023). It also briefly describes key strategic documents for regions fully or partially included in the Arctic Zone of the Russian Federation (AZRF): both the strategies and the corresponding programs for their implementation³. One of the primary objectives is to increase life expectancy in the regions.

The study (Stepanov, 2024) described a regression model constructed by the author using panel data from the Volga Federal District, which links life expectancy to a number of explanatory variables (economic, medical-social, etc.). This model performs well for many other regions; its applicability has been demonstrated for two regions of the North-Western Federal District (NWFD)⁴ and, similarly, for the Central Federal District (CFD) (Stepanov, 2024). Following the analysis of data from 126 countries, a model similar to this one was developed in the article (Shtun, 2021).

Furthermore, the article (Novikov, 2022) noted that “a joint and comprehensive approach to the development of Arctic coastal territories, in conjunction with issues ... relating to improving the socio-demographic situation and the quality of life of the population, as well as environmental protection” offers promising prospects for addressing the challenges of AZRF development. In this regard, it is worth drawing attention to another model, constructed using data from 17 regions of the CFD, covering the five-year period prior to the recent pandemic⁵; it was developed based on findings from (Stepanov, Bobkov, Shamaeva et al., 2022). In this model, the dependent variable is an aggregated composite variable that characterizes the level of material well-being of the population (WBP) at a regional level. Its factor variables included a composite variable for infrastructure, a range of indicators measuring the digitalization of organizations’ activities, life expectancy for males (LEm), and others.

Given the strategic importance of regions fully or partially located in the AZRF, it would be of interest to apply these models jointly, selecting the Arkhangelsk Oblast as a case study. For comparison, it is useful to consider another AZRF region — the Republic of Karelia — as well as two neighboring regions and several others from the Siberian and Far Eastern Federal Districts. Almost all these regions had population densities similar to that of the Pomorye region (Table 4, see below). Moreover, in almost all cases, with the exception of Karelia, the ethnic Russian

² Website of the Government of the Arkhangelsk Oblast. URL: https://dvinaland.ru/gov/national_projects/demogr/ (accessed 24 July 2025).

³ Decree of the Government of the Russian Federation No. 484 dated March 30, 2021, “On Approval of the State Program of the Russian Federation ‘Socio-Economic Development of the Arctic Zone of the Russian Federation’” (as amended on September 24, 2024). URL: http://www.consultant.ru/document/cons_doc_LAW_381261/ (accessed 31 July 2025).

⁴ Stepanov V.S. On the Application of Regression Models to Regional Data: Population Quality of Life and Life Expectancy. Problems of Economic Growth and Sustainable Regional Development: Proceedings of the 10th International Scientific and Practical Internet Conference, May 19–21, 2025. Section 1. Paper 6. 5 p. Vologda: Vologda Research Center. URL: <http://econproblem.volnc.ru> (accessed 24 July 2025).

⁵ Ibid.

population share consistently exceeded 91.5%. In most regions, excluding those located east of the Ural Mountains, temperatures in January or July were comparable (based on 2017 and 2019 data, excluding Primorye, where temperatures were almost identical to those in Pomorye). In many cases, the urban settlement pattern resembles that of Pomorye: a regional capital of moderate size, followed by a city with a significantly smaller population, and then a series of towns with progressively smaller populations. The share of the urban population is quite similar across seven regions (only the Leningrad Oblast lags behind). The structure of the gross regional product (GRP) was also examined (Table 3, see below). In all eight regions, the share of the agricultural, forestry, and fisheries sectors in GRP ranges from 3.9% to 7.3%. The construction and energy sectors show similar levels of development (with the exception of two regions that stand out with higher figures), while the trade sector does not exceed 16% (it is higher in two regions of the Far Eastern Federal District); the transport sector is also well-developed (with only the Kostroma Oblast lagging slightly behind). The ICT sector typically accounts for 1.4%–2.4%, real estate — for 7.5%–11.5%, and the scientific-technical sector — for 1.6%–2.5% (with the Pomorye region showing a lower figure); the services and security sector contributes between 8.8% and 14.5% (except for the Leningrad and Vologda Oblasts). The education and healthcare sectors are well-developed in these regions. Many also recorded similar per capita GRP figures in 2019, indicating that the regions have a number of comparable characteristics. Interestingly, the proportion of the population living in poverty also varied slightly across the regions in 2023, ranging from 8.7% in the Kostroma Oblast to 10.2% in Karelia (compared to 6.8% for the Leningrad Oblast and 11.3% for the Tomsk Oblast).

Comparing these indicators makes it possible to select realistic benchmarks applicable to the Arkhangelsk Oblast. These can then be used to demonstrate, through a numerical example, what specific steps might have led to a slight increase in the region's aggregate well-being indicator in 2020 and to an increase in life expectancy in 2019. This example is purely illustrative, and the increments have been chosen so that the Pomorye region's graph for that year would run almost parallel to the Leningrad Oblast's graph.

Using a similar methodological approach, these two models can be applied to other regions within the AZRF or those located nearby: the Yamalo-Nenets Autonomous Okrug, the Khanty-Mansi Autonomous Okrug; the Republics of Karelia and Komi; the Tyumen, Tomsk and Irkutsk Oblasts; the Krasnoyarsk, Primorskiy and Khabarovsk Krai; and others. It is important to note that each Russian region is unique, making such generalizations rather conditional. Nevertheless, the specific characteristics of different regions are partially taken into account in Models 1 and 2 through dummy variables included in their specifications; therefore, the value of the constant in these models often varies from region to region.

The aim of this study is to describe the results of applying two regression models, developed using panel data from regions in Central Russia and the Volga region, in which the dependent variables are an aggregate indicator of population well-being and life expectancy. The

performance of these models and the dynamics of their factors are examined using data from the Arkhangelsk Oblast and several other regions of Russia.

The study's novelty lies in the application of an improved version of the author's model for the aggregate indicator of population well-being to Rosstat data collected in the Arkhangelsk Oblast and other Russian regions, with an analysis of the impact of its factor variables on the dependent endogenous variable. This improvement involves considering updated official Rosstat data, resulting in slight adjustments to the list of factor variables, all model b-coefficients, and certain time lags. Consequently, the model's accuracy has increased slightly.

Furthermore, a second model is applied to these regions for the first time, with a similar analysis of its factors regarding life expectancy at birth. Finally, an example is presented to illustrate how the models work, and a number of constraints for the Pomorye region are listed. The data analysis methodology can also be applied to some of the AZRF regions or their neighbors, as well as to other regions in the Central, North-Western, and Volga Federal Districts.

The performance of Model 2 was tested by the author across a significant number of regions of the Russian Federation during the periods 2011–2019 and 2021–2023. For the majority of regions — with the exception of those in the Arctic, the northern part of the Far Eastern Federal District, or a number of southern regions (the North Caucasus Federal District, etc.) — the results demonstrated high accuracy. Model 1 was applied to the eight regions under study as follows: first, the actual values of the dependent variable for the Vologda Oblast for 2018–2020 were obtained for its previous variant, and a dummy variable from the model was selected to ensure that the forecast point was close to the actual value⁶ (Fig. 3). Subsequently, similar procedures were carried out for the Arkhangelsk, Vologda, and Tomsk Oblast, the Republic of Karelia, and the Primorskiy and Khabarovsk Krai for 2018–2019.

The first part of the article describes the development of a model for an aggregated indicator of population well-being (specifically, the integral indicator of the well-being of the population, II WBP). The second part details the application of this model to statistics collected in the Pomorye region. It also presents graphs for several regions, two of which are partially located in the AZRF, as well as those bordering them. The third part analyzes the factor variables which, within the framework of Model 1, could improve the quality of life indicator under consideration in the Pomorye region, as well as in a significant number of other regions. The fourth part briefly examines the life expectancy indicator at the regional level and describes Model 2, which is applied to a number of regions within the Russian Arctic Zone and several adjacent ones, with a particular focus on the Arkhangelsk Oblast. An illustrative example for the Pomorye region is also presented here, demonstrating the projected increase in life expectancy (for 2019) and the change in the aggregated WBP variable (for 2020) that would result from improving certain factors

⁶ Stepanov V.S. On the Application of Regression Models to Regional Data: Population Quality of Life and Life Expectancy. Problems of Economic Growth and Sustainable Regional Development: Proceedings of the 10th International Scientific and Practical Internet Conference, May 19–21, 2025. Section 1. Paper 6. 5 p. Vologda: Vologda Research Center. URL: <http://econproblem.volnc.ru> (accessed 24 July 2025).

included in these models, primarily in previous years. The last part discusses the results and outlines the problem areas identified in this region.

Brief description of the stage of building a model of WBP using data from the CFD

Let us briefly describe the model of population's welfare (WBP model), which is regarded as one of the dimensions of the population's quality of life. First, according to the methodology (Aivazian, 2012), the integral indicator (II) of WBP was calculated by convolving the set of variables $x_1, \dots, x_p$; the variables themselves are listed in the study (Stepanov, Bobkov, Shamaeva et al., 2022), in which $p = 15$. We also provide the list of variables below (Table 1); the result of the grouping of variables carried out during the application of the methodology, as will be described further, is shown on the right.

Table 1

List of indicators for constructing the II WBP

	Indicator (variable)	Block No.
1	GRP _i for year t (per capita), divided by the ratio (SR_i / SR_{RF}), where i — the region number ^{*1)}	3
2	Retail turnover combined with the paid services volume in the region (calculated similarly)	3
3	CI/SR — purchasing power of per capita cash income (CI)	3
4	Share of household (HH) expenditure on food (incl. housing, utility, and fuel costs), %	2
5	Share of education expenditure in total household consumption expenditure, %	3
6	Average individual deposit in RUR accounts in the SBRF, as a share of SR	3
7	Average housing provision (total residential floor area per capita) [m ² /person]	1
8	Commissioning of total residential floor area in residential buildings per 1,000 population	1
9	Share of dilapidated and unsafe housing in the region's total housing stock, %	1
10	Integral indicator of housing stock amenities in the region — II HA ^{*2)}	1
11	Average provision of personal passenger cars (per 1,000 population)	3
12	Share of low-income population — number of residents with per capita CI below SR, %	2
13	Index of household (HH) financial security in the region ^{*3)}	2
14	Funds coefficient (C_f), calculated by income groups with 10% of rich and 10% of poor	4
15	Share of households (HH) with Internet access (among all HH) by the end of year t	2

* Notes: 1) SR_i , SR_{RF} — subsistence rate for the fourth quarter for the i -th region and the Russian Federation, respectively; 2) II HA is calculated using the methodology proposed by Aivazyan (2012) based on a set of indicators regarding housing amenities, as described by Stepanov (2022) (this index represents the first principal component: a linear combination of the shares of the total residential floor area equipped by year-end with running water, sewage systems, heating, hot water supply, bathtubs/showers, and mains gas or electric ranges); 3) the HH Index based on financial security (Table 1) is derived from the distribution of HHs published in tables based on Rosstat surveys of HH heads regarding their financial situation in year t ⁷.

The II WBP variable, which has an aggregated type, is calculated according to official Rosstat statistics collected in 17 regions of the CFD over 5 years⁸. This was done using correlation and component analysis methods, through their application to data with variables $x_1, \dots, x_p$. They

⁷ Household Income, Expenditure, and Consumption: Statistical Bulletin. Moscow, Rosstat. URL: <https://rosstat.gov.ru/folder/11110/document/13271> (accessed 15 August 2025).

⁸ Materials from the website of the Federal State Statistics Service of the Russian Federation (Rosstat). URL: <https://rosstat.gov.ru/> (accessed 11 August 2025).

form a table of initial data with observations, comprising p columns and n rows (in our case, $n = 85$). As a result of this stage of calculations, all indicators $x_1, \dots, x_p$ (Table 1) were divided into M blocks; simultaneously, the weighting contribution for the j -th block ω_j is determined, where $j = 1, \dots, M^9$. The value ω_j is taken to be proportional to the variance of the variable Y_j and the number of indicators p_j from the j -th block, according to the formulas from (Aivazian, 2012). The Y_j variable is the “block version” of the II WBP; this is usually the first principal component found from the covariance matrix of the variables in the j -th block: $x_1, \dots, x_{p_j}$ (they were first reduced to the same scale). These weights are used in the calculation of the summary indicator; the sum of all ω_j is equal to 1. The technology for working with data is similar to that given in (Stepanov, Bobkov, Shamaeva et al., 2022). The block-partitioning stage is necessary because the set of variables $x_1, \dots, x_p$ is usually heterogeneous, and therefore the principal component method is applied in a block form for such tasks. In other words, it is assumed that the correlation coefficient matrix for all p variables can be approximately replaced by its block-diagonal analogue (as can the covariance matrix) (Stepanov, Bobkov, Shamaeva et al., 2022). As a result, the number of blocks $M = 4$, and the values of the weights $\omega_1, \dots, \omega_4$ were initially equal to those given in the work¹⁰. However, in subsequent Rosstat publications¹¹, the values of many standard of living variables (in its statistical collections) changed quite significantly, and after processing these updated data, the following values were obtained: $\omega_1 = 0.24$; $\omega_2 = 0.2544$; $\omega_3 = 0.373$ and $\omega_4 = 0.132$. In order to clarify: block 1 is related to the housing stock and the provision of housing for citizens, taking into account its quality ($p_1 = 4$); block 2 combined poverty indicators ($p_2 = 4$); block 3 forms income indicators: GRP, etc. ($p_3 = 6$); block 4 contains the fund coefficient, after its normalization ($p_4 = 1$) (see Table 1). In other words, the importance of block 4, which measures social stratification by income, increased according to ω_4 , the weight of ω_3 of the block with GRP decreased, and the weight of ω_2 for the housing block changed.

The weights ω_j are used in the calculation of the “aggregate II” of the WBP (Aivazian, 2012; Stepanov, Bobkov, Shamaeva et al., 2022), denoted below as Y , and its estimate — as $Y^{(t)}$. Specifically: for the i -th set of observations $x_1, \dots, x_p$ over a given region of the country, the value of Y is calculated as the difference: $Y = 10 - \sqrt{\sum_{j=1}^M \omega_j \cdot (10 - Y_j)^2}$, according to (Stepanov, Bobkov, Shamaeva et al., 2022). The index i here, as well as below, is not shown to simplify the notation. Under the root sign is the value Y_j — an indicator for the j -th block, or “block II” (Aivazian, 2012). It is obtained by linear convolution of all p_j variables $x_1, \dots, x_{p_j}$ that formed the composition of the j -th

⁹ Stepanov V.S. On the Application of Regression Models to Regional Data: Population Quality of Life and Life Expectancy. Problems of Economic Growth and Sustainable Regional Development: Proceedings of the 10th International Scientific and Practical Internet Conference, May 19–21, 2025. Section 1. Paper 6. 5 p. Vologda: Vologda Research Center. URL: <http://econproblem.volnc.ru> (accessed 24 July 2025).

¹⁰ Ibid.

¹¹ Materials from the website of the Federal State Statistics Service of the Russian Federation (Rosstat). URL: <https://rosstat.gov.ru/> (accessed 11 August 2025).

block, where $1 \leq p_j < p$. The new variables Y_j and Y take values from $[0, 10]$, according to (Aivazian, 2012). Thus, the value $Y = 10$ corresponds to a hypothetical region (reference region) which could have the most favorable values for each of $x_1, \dots, x_p$. Conversely, if $Y = 0$, this corresponds to the situation where all $x_1, \dots, x_p$ could turn out to be the worst possible (for another hypothetical region). Ultimately, Y is calculated as the weighted Euclidean distance between a pair of points in 4-D space: $(10, \dots, 10)^T$ — for the reference region and $(Y_1, Y_2, Y_3, Y_4)^T$, obtained by calculations based on the values of the variables $x_1, \dots, x_p$ for the i -th observation. This was previously illustrated in (Stepanov, 2019) for the option in which the number of blocks is $M = 3$.

The initial vector of observations at the “model building” stage was a set of values $x_1, \dots, x_p$ for a certain area of the CFD, taken in the year $t \in \{2015, \dots, 2019\}$. Each of these variables was first scaled to the range $[0, 10]$ by means of a simple linear scaling operation. Furthermore, the calculation of the aggregated variable Y_j for the j -th block is carried out using the methodology (Aivazian, 2012), based on a minor modification made to one of the principal component analysis formulas (Stepanov, Bobkov, Shamaeva et al., 2022). In other words, if $p_j > 1$, then the value Y_j is most often the first principal component for all p_j variables $x_1, \dots, x_{p_j}$ or (much less often) some approximation of it (Stepanov, Bobkov, Shamaeva et al., 2022; Aivazian, 2012). In our case, this took place for blocks 1–3, while the last block includes a single indicator of income stratification calculated based on 10% population groups (i.e., “funds coefficient”)^{12,13} (Stepanov, Bobkov, Shamaeva et al., 2022).

A methodologically similar calculation was carried out using 10 indicators other than $x_1, \dots, x_p$; describing the development of road and transport infrastructure in the region (Stepanov, 2022). These infrastructure indicators also formed their own blocks. These blocks, along with the method for calculating “weights” for the regions of the Volga Federal District (VFD), were presented in a brief report¹⁴. The highest weight, approximately 0.47, was assigned to the block comprising the density of public-use railways and similar hard-surfaced roads, the share of roads with improved hard surfacing, and the density of navigable river routes. A second block, with a weight of approximately 0.3, included regional and inter-municipal roads meeting standard requirements, the share of “asphalted roads”, and regional road traffic capacity. The other two blocks took into account road safety and the availability of public buses to the population. Consequently, an aggregate variable — the transport infrastructure integral indicator (II TI) — was calculated annually for each region of the CFD. It takes values in the range $[0, 10]$ and

¹² Stepanov V.S. On the Application of Regression Models to Regional Data: Population Quality of Life and Life Expectancy. Problems of Economic Growth and Sustainable Regional Development: Proceedings of the 10th International Scientific and Practical Internet Conference, May 19–21, 2025. Section 1. Paper 6. 5 p. Vologda: Vologda Research Center. URL: <http://econproblem.volnc.ru> (accessed 24 July 2025).

¹³ Materials from the website of the Federal State Statistics Service of the Russian Federation (Rosstat). URL: <https://rosstat.gov.ru/> (accessed 11 August 2025).

¹⁴ Stepanov V.S. Econometric Model for Estimating an Aggregated Welfare Variable in the Volga Oblast. Problems of Economic Growth and Sustainable Territorial Development: Proceedings of the 10th International Scientific and Practical Internet Conference, May 17–19, 2023. Vologda: Vologda Research Center; 2024: 180–184. URL: <https://elibrary.ru/nhydez> (accessed 31 July 2025).

subsequently serves as the factor variable X_1 in the model specification.

Constructing aggregate and block-level indicators (using the aforementioned variants for WBP and TI) and analyzing their dynamics over time (as the reference year t increases) for a given region make it possible to produce illustrative graphs, such as those shown in Figures 5–7 in (Stepanov, 2019). Studying the dynamics of block indicators Y_j over t makes it possible to identify problem areas (“bottlenecks”) within the list of indicators $x_1, \dots, x_{pj}$ for a given block. This approach was proposed in the methodology set out in (Aivazian, 2012). For example, it was applied to the Republic of Crimea (Stepanov, 2019), and a similar analysis was conducted for the Arkhangelsk Oblast (results are presented in the “Discussion” section).

Subsequently, a key concept proposed by (Aivazian, 2012) was implemented: using econometric methods to establish a link between the II WBP and a set of variables directly or indirectly influenced by policies pursued in the region and/or country. Such an approach could be of interest to regional authorities if they took it into account when formulating their development strategy. Ultimately, a regression model with a variable structure and 14 factors in its specification was constructed using panel data from the CFD. For this model, the adjusted coefficient of determination $R^2_{adj} \approx 96.7\%$ with a standard error $RMSE = 0.22$ and a mean absolute percentage error $MAPE = 4.0(\pm 3.2)\%$ (Carlberg, 2017). In other words, this regression model explained a high proportion of the variation in Y around the mean value calculated across all CFD regions over the five-year period.

Research results and discussion

Application of the well-being model to data from the Arkhangelsk Oblast and other areas

The Arkhangelsk Oblast is partially included in the Arctic Zone of the Russian Federation, and the development of information infrastructure in AZRF territories is a priority task (Kuratova, 2023). This region is strategically important to the Russian government due to its geopolitical and economic position (Kuznetsova, Vasilyeva, 2023). When applied to data from the Arkhangelsk Oblast, the model described above can be represented as follows:

$$Y^{(t)} = -8,834 + 0,364X_1 + 0,0285X_2 + 0,072X_3 + 0,14X_4 - 0,037X_5 + 0,77(X_6)^{0.5} + 0,139X_7, \quad (1)$$

where $Y^{(t)}$ — II WBP for year t , previously constructed by aggregating variables $x_1, \dots, x_p$;

X_1 — TI factor, derived in a similar manner and taken with a lag of $\tau = 1$ year^{15,16} (Stepanov, 2022);

X_2 — number of PCs per 100 employees in organizations with Internet access¹⁷, $\tau = 2$ years;

¹⁵ Stepanov V.S. On the Application of Regression Models to Regional Data: Population Quality of Life and Life Expectancy. Problems of Economic Growth and Sustainable Regional Development: Proceedings of the 10th International Scientific and Practical Internet Conference, May 19–21, 2025. Section 1. Paper 6. 5 p. Vologda: Vologda Research Center. URL: <http://econproblem.volnc.ru> (accessed 24 July 2025).

¹⁶ Stepanov V.S. Econometric Model for Estimating an Aggregated Welfare Variable in the Volga Oblast. Problems of Economic Growth and Sustainable Territorial Development: Proceedings of the 10th International Scientific and Practical Internet Conference, May 17–19, 2023. Vologda: Vologda Research Center; 2024: 180–184. URL: <https://elibrary.ru/nhydez> (accessed 31 July 2025).

X_3 — share of organizations in the region using specialized software (such as CRM, ERP, or SCM systems — CES^{18,19,20}) in year $t-4$; the lag is $\tau = 4$ years, the factor is expressed in %;

X_4 — share of organizations using RFID technologies in year $t-2$ ^{21,22}, in %;

X_5 — level of subsidies for the region's consolidated budget (BT/GRP), expressed as a percentage for year $t - \tau$, where BT (budget transfers) refers to non-repayable budget receipts²³ (i.e., the lag $\tau = 2$);

X_6 — variable calculated as the proportion of per capita GRP attributable to the economic sector comprising forestry, agriculture, and the fishing industry for year t ; it is calculated relative to the subsistence minimum rate (SR)²⁴ of the population in the region under consideration for year t ;

X_7 — life expectancy at birth for males (LE_M) in the year preceding year t (i.e., here $\tau = 1$). Only X_6 enters equation (1) simultaneously with $Y^{(t)}$.

The indicators $X_2, \dots, X_4$ without taking lags into account, were also examined in (Kuratova, 2023; Akberdina, Naumov, Krasnykh, 2023). The male infant life expectancy indicator (LE_M) proved to be more informative than the overall LE at the regional analysis stage, that is, during the process of constructing a fixed-effects regression model (with 14 factors). This was found as follows: when the LE_M variable is included instead of the LE factor, the coefficient of determination R^2 increases significantly, and the Student's t -statistic for LE also becomes significant. The wide disparity in life expectancy between the male and female populations of Russia is due to a combination of factors (the consequences of the 1941–1945 war and a number of other factors). This gender gap has a negative impact on the economy and the social sphere in the regions of the Russian Federation.

The performance of model (1) as applied to data from the Arkhangelsk Oblast and the Republic of Karelia, as well as two neighboring regions, is shown in Fig. 1. Some of the districts and towns in these regions are part of the AZRF. The figure also displays actual $Y^{(t)}$ values for 2018–2019; these were derived from regional values of variables $x_1, \dots, x_p$ and calculated using the previously described methodology, alongside the initial set of 85 observations. When calculating the estimate $Y^{(t)}$ by substituting values for $x_1, \dots, x_p$ into equation (1), the values of the constants may vary between regions (i.e. a model with 14 variables was effectively used).

¹⁷ Materials from the website of the Federal State Statistics Service of the Russian Federation (Rosstat). URL: <https://rosstat.gov.ru/> (accessed 11 August 2025).

¹⁸ Ibid.

¹⁹ Note: ERP system integrates information and functions across an organization's departments; CRM system manages customer relationships; SCM system manages the organization's supplier orders; RFID is a computer technology for the automatic identification of objects.

²⁰ Digital Economy Indicators: 2021. Moscow: HSE, 2021. <https://doi.org/10.17323/978-5-7598-2385-8>

²¹ Materials from the website of the Federal State Statistics Service of the Russian Federation (Rosstat). URL: <https://rosstat.gov.ru/> (accessed 11 August 2025).

²² Digital Economy Indicators: 2021. Moscow: HSE, 2021. <https://doi.org/10.17323/978-5-7598-2385-8>.

²³ Materials from the website of the Federal State Statistics Service of the Russian Federation (Rosstat). URL: <https://rosstat.gov.ru/> (accessed 11 August 2025).

²⁴ Ibid.

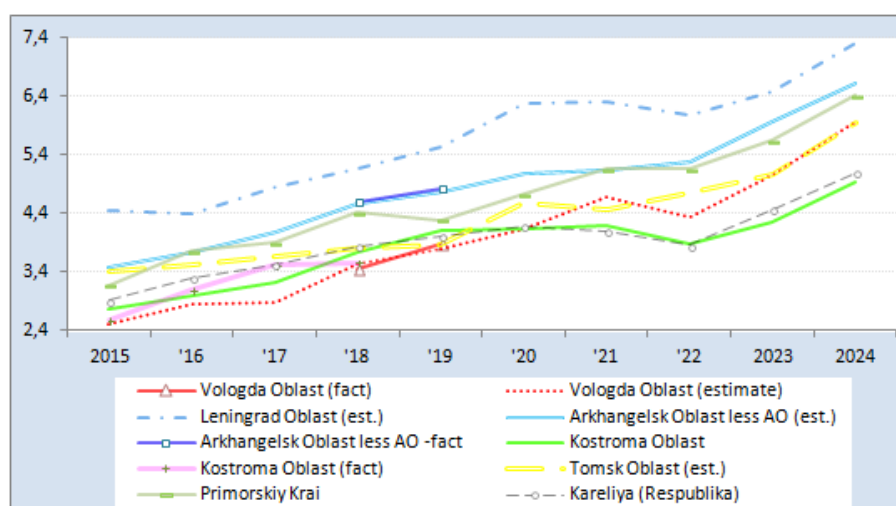


Fig. 1. Dynamics of the II WBP for seven regions across the NWFD, CFD, SFD, and FEFD²⁵.

Graphs showing $Y^{(t)}$ estimates for the Primorskiy Krai and the Kostroma Oblast are also provided. Although both regions have population densities more than four times higher than that of Pomorye, they share several characteristics with this northern area (as noted in the introduction). A graph for the Toms Oblast, a leader in innovation, is also shown; however, the local natural and climatic conditions are considered uncomfortable.

A comparison of the graphs reveals that the model-based $Y^{(t)}$ estimates for the Arkhangelsk Oblast and the Primorskiy Krai exhibit similar dynamic behavior over t . It is interesting to note that a number of settlements and four districts in the Primorskiy Krai are classified as part of the Far North. It is evident that, since 2018, the graph for Karelia has almost coincided with that of the Kostroma Oblast.

Analysis of factors influencing $Y^{(t)}$: the Arkhangelsk Oblast and others

An examination of the elasticity coefficients from the original model (from which formula (1) was derived) indicates that the primary contributions came from the factors LE_M , X_1 , X_6 , followed by measures related to the digitalization of organizational activities: X_2 , CES , $RFID$. We proceed to examine the factors X_1 , X_2 , CES , $RFID$ and LE . Table 2 (columns 2–5) presents the four-year trend for factor X_1 in Pomorye alongside data from six other regions across the North-Western, Central, and other federal districts.

Table 2

Dynamics of the II TI for seven regions and the transport accessibility index in 2018²⁶

Region	2015	2016	2017	2018	TAI	TAI rank
1	2	3	4	5	6	7
Arkhangelsk Oblast	3.0	3.0	3.0	3.0	7.0	62
Vologda Oblast	4.13	4.09	4.54	4.56	11.2	33
Komi Republic	4.1	4.04	4.07	4.02	7.03	61
Republic of Karelia	4.9	4.95	5.17	5.22	7.73	58
Kostroma Oblast	3.78	3.78	3.756	3.77	13.0	17

²⁵ Author's calculations are based on official data from Rosstat publications: materials from the website of the Federal State Statistics Service of the Russian Federation (Rosstat) and their visualization. URL: <https://rosstat.gov.ru/> (accessed 11 August 2025).

²⁶ The author's calculations are presented in columns 2–5; columns 6 and 7 present the results of other authors.

Tomsk Oblast	3.66	3.62	3.78	3.76	7.57	59
Primorskiy Krai	4.4	4.36	4.46	4.4	5.57	69

Columns 6 and 7 present the transport accessibility index (TAI) from (Lavrinenko, Romashina, Stepanov et al., 2019) and its ranking for 2018. The values of X_1 shown on the left are for a number of regions situated near the Arkhangelsk Oblast and the AZRF, as well as two other regions that share certain characteristics with Pomorye: similar winter and summer air temperatures and comparable per capita GRP figures (in 2019, Karelia ranked 31st, Pomorye 33rd, and Vologda 34th in Russia). Population densities in Karelia and Pomorye are relatively comparable, and both regions lie partially within the AZRF; urbanization rates are also similar: 79.2% of urban population in Karelia, 77.4% in Pomorye, and 72.4% in Vologda. The largest cities in these regions had the following populations: Petrozavodsk — 279,000; Arkhangelsk — 350,000; and Cherepovets — 318,000 (as of early 2018); each region had 20–22 urban settlements. The two largest cities in Pomorye have a combined population of 523,000, compared to 630,000 in the Vologda Oblast (whereas in Karelia, the figure was only 309,000). Beyond the top three, the remaining urban settlements in these regions are small (with populations of 38,000 or less). If the area of the Karelian territory is divided by the number of its rural settlements, the result is approximately 2,100 km²; if the same calculation is carried out for Pomorye, the result is 2,350 km². A comparison of the sectoral structure of the GRP in these three regions for 2019 reveals no significant differences (Table 4). While the Vologda Oblast lacks an extractive industry, it successfully compensates for this absence through four other sectors: manufacturing, construction, trade, and scientific-technical activities. Furthermore, because the manufacturing sector here is focused on metallurgy, the chemical industry, pharmaceutical production and others (Table 5), this region significantly outperformed Pomorye in 2018 in terms of both the value of the CDI and its ranking. Finally, regarding the level of innovation activity, the Vologda Oblast has been rapidly outpacing the corresponding figures for Pomorye since 2013 (Fig. 6).

For instance, the Leningrad Oblast, together with St. Petersburg, has TAI value of 15.1 and would rank 7th in Table 2, whereas Pomorye is among the outsiders. The benchmark region, defined by the ten variables aggregated to derive this II TI, has an X_1 value of 10. In other words, it would exhibit the most favorable values for all ten variables among the territories analyzed in the study (Stepanov, 2022). Its roads would be in a standard-compliant (or near-compliant) condition, the density of public road and rail networks would be attractive, water transport would be optimally developed, and so on.

It has previously been noted that a formalized approach to calculating the TAI is important for practical applications (Lavrinenko, Romashina, Stepanov et al., 2019). This paper also provides references to studies on the transport accessibility of a territory. This is defined as the ability to reach a region's territory using various types of infrastructure. Another review of research in the field of transport infrastructure is presented in (Stepanov, 2022). However, neither article took maritime transport into account, and (Stepanov, 2022) also excluded air transport. Another

difference between these two works lies in the methodology for calculating the TAI when compared with that used for the II TI. Thus, in (Lavrinenko, Romashina, Stepanov et al., 2019), the TAI value is estimated by accounting for all transport costs, including actual monetary expenditures and travel time to a given region; these factors are considered across various modes of transport and for citizens residing in all regions of the Russian Federation. The methodology for calculating the II TI value is based on the construction of integral indicators as described in (Aivazian, 2012). This approach employs a combination of principal component analysis and correlation analysis, making it quite versatile. For example, it was used by Dao Mai Han (2007) — a postgraduate student at the Central Economics and Mathematics Institute of the RAS (CEMI) from Vietnam — when modelling foreign trade for that country (the fisheries sector). The list of variables in the article (Stepanov, 2022) was limited to regional data from Rosstat; if its website had provided annual data on air and sea transport, these would also have been used in calculating the TI index.

Thus, considering the Primorskiy Krai case in Table 2, this FEFD region is remote from the central part of the Russian Federation. Consequently, a trip to Primorye is costly and time-consuming for the average Russian, resulting in TAI rank of 69. On the other hand, the region is characterized by having only 74 rural settlements across a territory of 164.7 thousand km², and their ratio is 2.23, which is only slightly lower than that of the Pomorye case. However, Primorye is more developed in terms of urban centers: its capital has a population of 600,000, and there are three towns with over 100,000 residents, five towns with populations exceeding 40,000, and so on. Furthermore, due to its proximity to Japan (which is why reliable Japanese cars, albeit not new ones, are more affordable in Primorye), residents are better equipped with private vehicles: 447 versus 332 (based on 2019 data). This is probably why the condition of the roads here is closer to the standards, and their density is considerable. There are also many rivers, a large lake and a well-developed water transport system; there is a good railway network. Hence: $X_1 \approx 4.4\text{--}4.5$ (this represents the II TI).

An examination of the graphs for variable X_2 (Internet access) for the average value across all regions of the CFD regions over a nine-year period with the corresponding graphs for four NWFD regions, the Kostroma and Tomsk Oblasts, and Primorskiy Krai reveals that the graph for the Kostroma Oblast is very close to this average, whereas the graph for the Tomsk Oblast is significantly higher, ranging from 38 to 55 per 100 employees (Fig. 2).

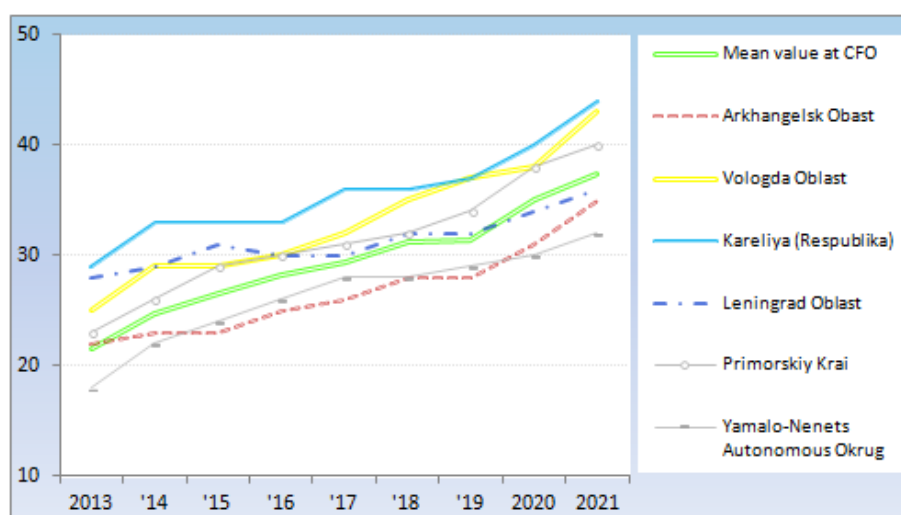


Fig. 2. Internet access in organizations across six regions and the average level in the CFD (number of PCs)²⁷.

It is evident that the situation in the Yamalo-Nenets Autonomous Okrug and the Arkhangelsk Oblast was rather unfavorable from 2013–2014 to 2020. This variable is examined in the regions of the AZRF in (Kuratova, 2023), where it is designated as X_{20} ; it also appears labeled as X_2 in Table 5 of the same study. It follows from the information provided and Table 5 that the provision of one computer with internet access for every 100 employees was a bottleneck in Pomorye, similar to the situation in the Yamalo-Nenets Autonomous Okrug. Regarding Internet usage, it is worth noting that the rate of internet access in Pomorye organizations has remained virtually stagnant since 2016. Moreover, since 2015, broadband access in the region has declined noticeably when compared to the CFD, a trend particularly significant for rural settlements in Pomorye. While the Vologda Oblast's figures were close to this average between 2013 and 2018, the corresponding indicator for Pomorye has lagged behind by 3–4% annually since 2015.

An analysis of the CES indicator for the period 2011–2019 reveals that, in this respect, organizations showed relatively little variation across the regions under consideration, with one trend often dominating: organizations in Pomorye experienced a temporary decline in CES usage during 2016–2017. However, following the pandemic and the start of the special military operation in Donbas, the frequency of CES usage across the seven regions began to diverge significantly, with Pomorye organizations falling behind²⁸.

In terms of trends in RFID usage, the situation in Pomorye is more favorable (Fig. 3). However, there is a noticeable gap between Pomorye and the innovative Tomsk Oblast, as well as the Russian average.

²⁷ Created by the author based on the statistical compilation "Regions of Russia: Socio-Economic Indicators" and materials from the website of the Federal State Statistics Service of the Russian Federation (Rosstat). URL: <https://rosstat.gov.ru/> (accessed 11 August 2025).

²⁸ Materials from the website of the Federal State Statistics Service of the Russian Federation (Rosstat). URL: <https://rosstat.gov.ru/> (accessed 11 August 2025)

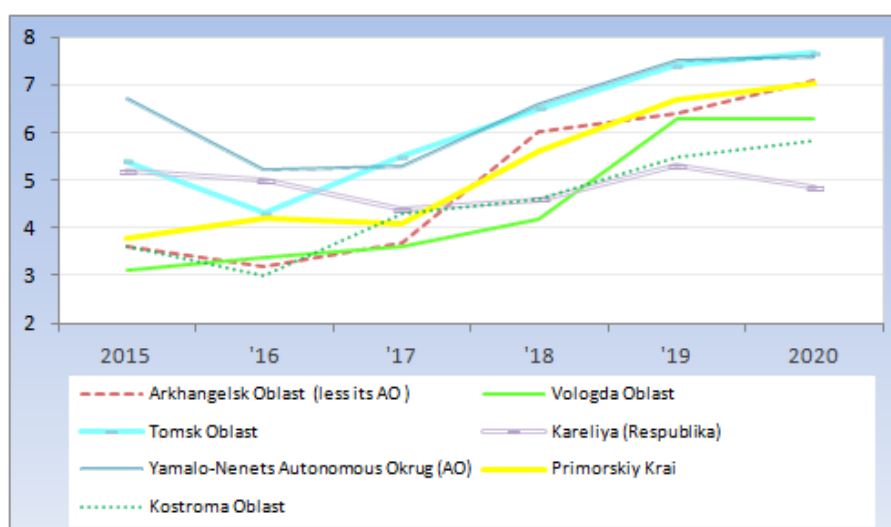


Fig. 3. Frequency of RFID technology usage in regions of the NWFD and other districts (%)²⁹.

It is worth noting that the Tomsk and Leningrad Oblast have almost always dominated; for the latter, the RFID adoption rate ranged from 5% to 6.5% between 2015 and 2020. This is even more pronounced in the economically powerful regions of Western Siberia — the Yamalo-Nenets Autonomous Okrug (YaNAO) and the Khanty-Mansi Autonomous Okrug (KhMAO), with the latter showing a higher share of RFID adoption than the YaNAO. For comparison, the RFID share in organizations in some European countries in 2018 was as follows: for Hungary, Denmark, Romania and the Russian Federation — 7% each; the Czech Republic and the United Kingdom — 8% each; Latvia — 9%; Lithuania — 10%; France — 11%; Estonia — 12%³⁰.

A comparison of the X_6 factor values across the regions under review reveals that the situation in Pomorye is quite favorable. Only in terms of indicator X_5 , which measures budget subsidies, it lags behind the aforementioned regions during the period 2015–2023. For instance, in 2017, the X_5 value for Pomorye was 3.4%, whereas for Primorye it was 2.64% and for the Tomsk Oblast — 2.3%. A comparison of the levels of budget subsidies from Primorye and Pomorye over the period 2013–2021 revealed that it was only in 2014 and 2018 that this subsidy measure decreased for Pomorye. However, in the remaining seven years, the region was more heavily subsidized: by approximately 20%. In other words, Pomorye's consolidated budget was generally less self-funded than that of the Primorskiy Krai. Nevertheless, in the cases of Karelia and Kostroma, budgetary provision was even worse: the X_5 values were 5.27% and 3.97%, respectively. Thus, the Karelian budget was the least self-sufficient, followed slightly better by the Kostroma budget. Below, we present a range of data on the life expectancy (LE) indicator for the entire population, which is close to X_7 .

²⁹ Created by the author based on the statistical compilation "Regions of Russia: Socio-Economic Indicators" and materials from the website of the Federal State Statistics Service of the Russian Federation (Rosstat). URL: <https://rosstat.gov.ru/> (accessed 11 August 2025).

³⁰ Table 2.1.21 "Information Society: Key Characteristics of the Subjects of the Russian Federation", 2019. Statistical compilation, Rosstat, 2019. URL: https://rosstat.gov.ru/storage/mediabank/info-ob_reg2019_405742.pdf (accessed 15 August 2025).

Analysis of factors influencing LE: the Arkhangelsk Oblast and others

A model, originally developed using 84 observations across the Volga Federal District (VFD) regions and estimated using pooled regression, helps to analyze the possible causes of variations in life expectancy (LE) across the regions of the Russian Federation. This is a regression model with a variable structure that incorporates lags for several factors; its constant varies by region based on changes in the model's dummy variables. Subsequently, measures of the population's physical activity and investment in healthcare were added to the list of factors, while the sample size increased to $n = 112$. The model was then further refined: some factors were replaced by others, and the sample size now stands at $n = 140$ (Stepanov, 2024). One of the new factors better accounts for the negative impact of alcohol and drugs, while other factors included the rate of unnatural mortality (deaths from external causes), the level of urbanization, and others. In essence, the improvements involved increasing the panel data sample size and making minor adjustments to the list of explanatory variables and the values of some of their lags. As a result, the model's quality metric rose to $R^2_{adj} \approx 97\%$; the standard error (RMSE) was 0.29, and the approximation error (MAPE) was 0.31 (± 0.22)% based on calculations across all n observations.

The model can be useful in developing measures aimed at increasing LE in many regions of the country. Thus, average elasticity coefficients have been calculated for it (Carlberg, 2017). It has been found that a reduction in the Gini index, a measure of social stratification by cash income (CI), is of paramount importance for increasing LE in the VFD^{31,32}. The next factors are the incidence rates of alcoholism and drug addiction, followed by the ratio $med(CI)/SR$ ^{33,34} (Stepanov, 2024). When calculating the numerator of this ratio, median income is used; in other words, the distribution of CI across eight population strata in the current year t is taken into account. The next indicators are the level of physical activity amongst the population and the proportion of urban residents; these are followed by the availability of doctors in the area and the external mortality rate. An increase in the value of $med(CI)/SR$, together with a decrease in Gini coefficient values, contributes to a reduction in the level of chronic stress amongst a section of the population³⁵. This will significantly reduce the consumption of cigarettes, alcohol and drugs; men are more prone to such behavior (Stepanov, 2024; Stepanov, Rybkina, Orlova, 2023).

Based on these results, data from Pomorye and 7–8 other regions were analyzed using a methodology similar to that described above. A model scenario is then proposed, using the indicator values for this area listed in rows 1–9 of the table below. When applying Model 2, we assume that the value of factor X_7 from equation (1) rises slightly to reach the value shown in row

³¹ Materials from the website of the Federal State Statistics Service of the Russian Federation (Rosstat). URL: <https://rosstat.gov.ru/> (accessed 11 August 2025).

³² "Rich and Poor" (from a conversation with Prof. A.Yu. Shevyakov). *In the World of Science*. 2005; 7: 73–79.

³³ Materials from the website of the Federal State Statistics Service of the Russian Federation (Rosstat). URL: <https://rosstat.gov.ru/> (accessed 11 August 2025).

³⁴ "Rich and Poor" (from a conversation with Prof. A.Yu. Shevyakov). *In the World of Science*. 2005; 7: 73–79.

³⁵ Ibid.

10. The application of Model 2 to the Vologda and Leningrad Oblasts is illustrated in the paper³⁶. The dynamics of LE in eight Russian regions during the decade preceding the pandemic are shown below (Fig. 4).

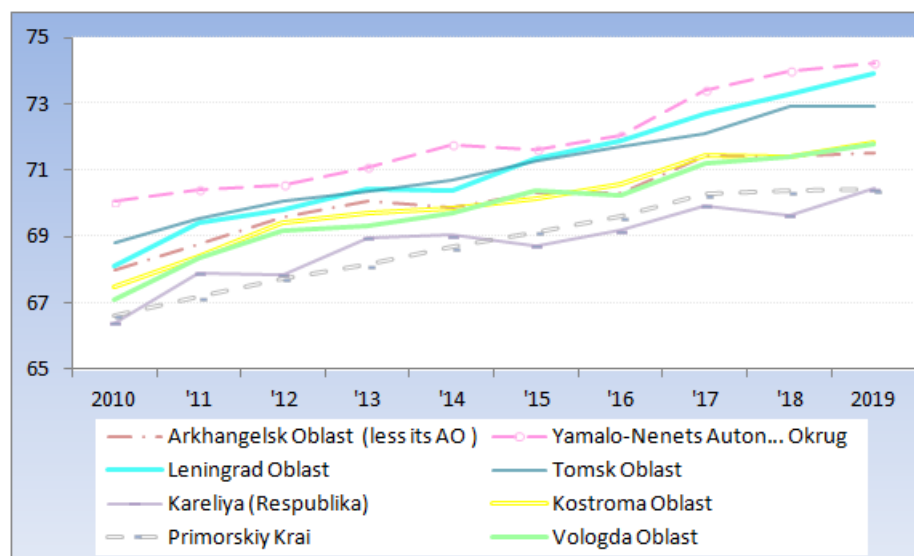


Fig. 4. Dynamics of LE in eight regions across the NWFD, CFD, FEFD, UFD, and SFD; years³⁷.

It is evident that during the period 2010–2019, the Yamalo-Nenets Autonomous Okrug and the Primorsky Krai, together with the Republic of Karelia, were the outliers at both the top and bottom of the distribution. Fig. 4 shows how the Leningrad Oblast curve occasionally caught up with that of the Yamalo-Nenets Autonomous Okrug, and reveals that LE values in the Vologda and Arkhangelsk Oblasts were very similar from 2014 onwards. It is also evident that the Arkhangelsk Oblast trend shows a noticeably shallower slope as the year t progresses from 2014 onwards. Actual LE values for these years, covering the AZRF regions and the country as a whole, were presented in Table 2 in (Provorova, Smirennikova, Ukhanova, 2024). It clearly shows that LE was above the national average only for residents of the Yamalo-Nenets Autonomous Okrug between 2005 and 2019. Meanwhile, LE figures for the Murmansk and Arkhangelsk Oblasts were slightly below the Russian average, while all other AZRF regions lagged even further behind. This is attributed, in particular, to the adverse impact of the harsh climate on the health of populations permanently residing in or near the AZRF regions (Provorova, Smirennikova, Ukhanova, 2024).

Following an analysis of the series of graphs and the above, let us provide an example.

Example: a model-based change in factors in Pomorye with estimates for 2019 and 2020

Table 3 shows how positive changes in the set of factor variables considered for both models could contribute to an improvement in the LE value for the Arkhangelsk Oblast in 2019, as

³⁶ Stepanov V.S. On the Application of Regression Models to Regional Data: Population Quality of Life and Life Expectancy. Problems of Economic Growth and Sustainable Regional Development: Proceedings of the 10th International Scientific and Practical Internet Conference, May 19–21, 2025. Section 1. Paper 6. 5 p. Vologda: Vologda Research Center. URL: <http://econproblem.volnc.ru> (accessed 24 July 2025).

³⁷ Created by the author based on the statistical compilation “Regions of Russia: Socio-Economic Indicators” and materials from the website of the Federal State Statistics Service of the Russian Federation (Rosstat). URL: <https://rosstat.gov.ru/> (accessed 11 August 2025).

well as its II WBP value in 2020.

Table 3

Example with actual and forecast values for the Arkhangelsk Oblast³⁸

Factor variables		Variable values in the two models	
		Fact	Model
1		2	3
1	Gini index of income inequality in 2019	0.364	0.359
2	Value of $\ln(\text{med}(CI)/SR)$ in 2019	0.79	0.82
3	Number of people with alcoholism in 2017	932.4	885.8
4	Incidence of alcoholism and drug addiction		5% decline
5	Volume of atmospheric emissions of pollutants in 2016, kg/capita		3% decline
6	Share of employed people with higher education in 2018, %	27.4	28.77
7	Physical activity per 1,000 inhabitants, 2019	350.2	367.7
8	External mortality rate in 2019	120.5	115.7
9	$\ln(\text{BadWater})$ — % of substandard water samples (from the distribution network)	2.6734	2.5665
10	Value of variable X_7 (male life expectancy) in 2019, years	65.94	66.29
11	Transport infrastructure indicator in 2019, points	3.0	3.06
12	PCs with web access per 100 employees, units, in 2018	28	30
13	CES indicator for organizations in 2016, %	13.5	15.2
14	Use of RFID in organizations in 2018, %	6.0	6.1
15	Measure of regional budget subsidization in 2017, %	3.24	3.175
16	Estimate of $Y(t)$ for II WBP after substitution into formula (1)	5.077	5.344

Thus, if the following set of measures were implemented in Pomorye — a) reduce the 2019 Gini index to the average value for the Tomsk and Vologda Oblasts; b) reduce the level of alcoholism by 5%; c) reduce the logarithm of the proportion of substandard water samples taken from the water supply network in 2017 by 4%; d) reduce the logarithm of the volume of emissions from stationary sources of pollution (SSP) into the atmosphere per capita by 3% — it could be assumed that, as a result of some of these actions, the external mortality rate in Pomorye would decrease by, for example, 4% (Table 3). Implementing these measures would increase the calculated LE by 0.87%, bringing the 2019 figure to 72.54 years instead of the actual 71.91 years. Assuming that the related indicator of LE_M increases in the same proportion, the resulting value would correspond to the figure in row 10 (Table 3).

Let us now turn to modeling variable Y , or estimating $Y^{(t)}$, under the scenario where the region successfully implements the following set of steps: a) increasing factor X_1 by 2%; b) raising factor X_2 to the level of the Republic of Sakha (Yakutia); c) slightly increasing factor X_4 (or RFID); d) raising factor X_3 (CES) to the level of the Murmansk Oblast; e) reducing variable X_5 (representing the level of budget subsidies for Pomorye) by 2%, bringing it down to the level of the Primorsky Krai (row 15). If the values from column 3 (Table 3) are substituted into formula (1), $Y^{(t)}$ yields the value shown in Table 3, and the graph for the Pomorye region runs roughly parallel to the Leningrad Oblast graph (Fig. 1). As previously mentioned, this example is purely illustrative.

³⁸ Author's calculations.

Discussion of results and identification of problem areas for the Arkhangelsk Oblast

In accordance with Russia's strategy, spatial development challenges include³⁹: mismatch between the development level of transport infrastructure and the needs of the economy and population; infrastructure constraints; weak transport connectivity between regions and economic growth centers; insufficient integration of different modes of transport; and others.

The study (Zakolyukina, 2023) focused on analysing the factors hindering the effective functioning of transport infrastructure as a driver of regional economic growth. The literature review refers to the link between these infrastructure indices and quality of life (Zakolyukina, 2023). It describes studies involving the calculation of integrated infrastructure indices.

The importance of developing transport infrastructure, as well as improving logistics alongside the progress of the digital economy, was highlighted in a review article (Levina, Dubgorn, Fadeev et al., 2024). This requires the development of land transport networks as well as shipping routes, specifically the Northern Sea Route (NSR) and river transport lanes. Such measures would facilitate more efficient movement of freight and labor resources (Levina, Dubgorn, Fadeev, et al., 2024). The digital economy is generally defined as the segment of economic output generated through digital skills and equipment (telecommunications equipment, hardware, software) and the use of digital goods and services. Furthermore, the article provides a number of references to relevant studies.

The study (Kuznetsova, Vasilyeva, 2024) assessed the level of development of transport infrastructure in two regions of the AZRF and provided an overview of the regulatory and legal documents affecting economic activity. It was noted that the development of AZRF seaport infrastructure and the formation of a digital subsystem would proceed in parallel with the development of the Northern Sea Route. Thus, among the promising projects, the development plan for the port of Arkhangelsk and its transport hub, as well as the creation of a logistics hub for the transshipment of container cargo, were highlighted. Additionally, Table 2 in the same study (Kuznetsova, Vasilyeva, 2024) demonstrated that the proposed transport infrastructure development index for Pomorye was the lowest among the regions within the specified parts of the AZRF during 2019–2021. This aligns with the data in Table 1 (see above). Finally, Table 6 (Kuznetsova, Vasilyeva, 2024) presented various coefficients, such as the Engel coefficient, etc. Given that population density in the Arkhangelsk Oblast is lower than in the Murmansk Oblast and slightly lower than in Karelia, the data in Table 6 allow for the following specific conclusion: these coefficients for Pomorye were at a normal level when compared to regions with similar population densities, namely the Nenets Autonomous Okrug and the Krasnoyarsk Krai. Table 7 of the study also presents data on seaports, with Pomorye ranking among the leading regions. For instance, the port of Arkhangelsk is classified as a “large” port, similar to the port of Murmansk; it also

³⁹ Spatial Development Strategy of the Russian Federation until 2025: approved by Order of the Government of the Russian Federation No. 207-r dated February 13, 2019. URL: <http://static.government.ru/media/files/UVAIqUtT08o60RktoOXI22JjAe7irNxc.pdf> (accessed 31 July 2025).

possesses a significant advantage in the form of a railway connection. Furthermore, these cities possess significant airport facilities, as shown in Tables 11–13 (Kuznetsova, Vasilyeva, 2024). Consequently, it is concluded that the transport infrastructure in the western part of the Russian Arctic Zone contributes to the growth of the GRP and improves living conditions for the population. Currently, there is an insufficient level of transport provision in Pomorye, which was explained in (Kuznetsova, Vasilyeva, 2024) by the region's geographical characteristics, harsh climate, and low population density.

According to our calculations, the relatively low value of the II TI variable (Table 2) for Pomorye is linked to the high proportion of local, inter-regional and inter-municipal roads which, between 2015 and 2019, were in a condition below the standards, with their quality being the worst in the NWFD. It is also linked to the fact that this northern region ranks last in terms of density of its public railway network. Furthermore, Pomorye ranks second to last regarding the share of roads with a hard surface, ahead of only the Vologda Region; in terms of density of these roads, Pomorye also lags behind many others, followed only by the Murmansk Oblast and the Komi Republic. Other problems of the Arkhangelsk Oblast in 2013–2019 include a rise in the unemployment rate since 2016 (according to rankings based on 85 regions across the country), as well as a slightly increased level of poverty (ranked 24th in 2019, despite a noticeable decline since 2015). Many of the region's challenges stem from issues with transport infrastructure and territorial accessibility. The region has a high proportion of housing stock classified as unsafe (condemned), and in 2018, the share of dilapidated housing was also elevated. When comparing housing amenity indicators across all regions for 2018, Pomorye ranked 72nd in terms of household access to running water and 74th — to centralized heating. It also ranked a low 75th regarding household access to centralized gas supplies and/or electric stoves. Furthermore, the region ranks low on three other indicators — access to sewerage, a bath or shower, and hot water supply — with scores ranging between 61 and 69. Finally, the proportion of the population with a good education was relatively low. This probably explains why internet access in urban areas declined over time, and the proportion of broadband internet access in rural settlements remained low. It is worth noting that a study (Zemtsov, Demidova, Kichaev, 2022) used econometric methods to reveal that web access depends on household income and the population's average age and education level, while the use of ICT depends on factors such as access to the global internet and the business climate. Furthermore, the Pomorye region lags behind in terms of innovation.

The article (Blinova, Bylina, 2019), which analyzed correlations among variables across a sample of 78 Russian regions in 2015, revealed a significant finding regarding the rural population: indicators of housing amenities showed a strong correlation with life expectancy. Moreover, these correlations were even stronger with the factor “density of paved public roads”.

The research (Bogdanova, Saburov, Minchuk et al., 2024) analyzed key areas of digitalization in regional development that foster innovation in the rural territories of the western

part of the AZRF (using the Arkhangelsk Oblast and its autonomous district as a case study). In particular, the study considers the development of information and communications infrastructure, the introduction of digital services, and the development of digital skills among residents. It is emphasized that digital transformation is likely to have a positive impact on a number of areas of the region's life: the economy, the environment, the social sphere, as well as its governing bodies. Particular emphasis is placed on improving the population's quality of life in relation to the level of regional digitalization. The review of foreign studies presented here also notes the potential negative impact on quality of life (Bogdanova, Saburov, Minchuk et al., 2024). The "Strategy for the Socio-Economic Development of the Arkhangelsk Oblast until 2035" is also mentioned, which addresses a number of aspects relating to the digitization of society.

An analysis of the 42 regions that ranked above Pomorye in the "Digital Russia" index at the end of 2018⁴⁰ reveals that after excluding the two capital cities (Moscow and St. Petersburg), which significantly outperformed the other regions, the following scatter plot can be obtained for the remaining territories, including Pomorye (Fig. 5).

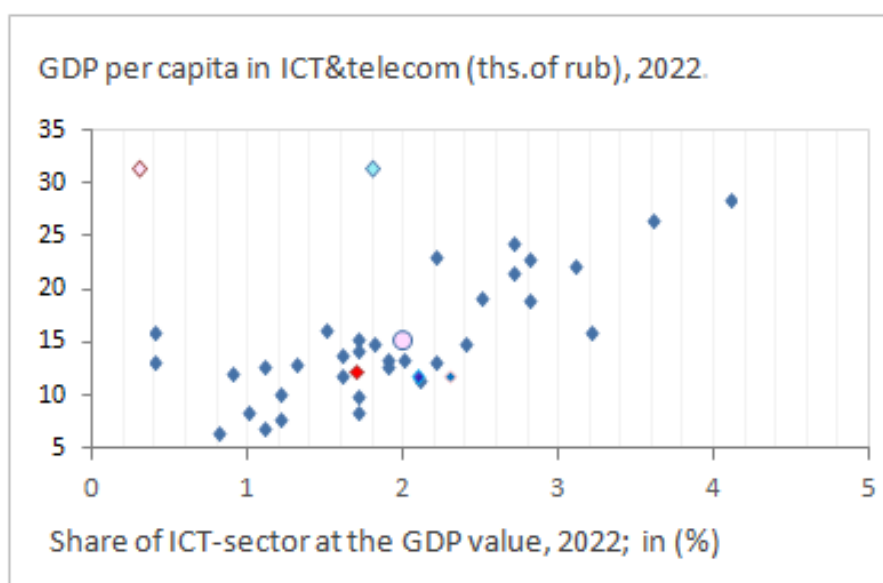


Fig. 5. Contribution of the ICT sector to the economy: Arkhangelsk Oblast and 40 other regions; thousand rubles⁴¹.

The y-axis shows the contribution of the "ICT and Communications" sector to the per capita GRP in 2022 (in thousand rubles). The x-axis indicates the share of this economic sector in GRP for that year. Four regions stand out significantly from the main cluster, forming an "ellipsoid-shaped cloud of points": two points at the top (the Yamalo-Nenets Autonomous Okrug and the Murmansk Oblast), and two on the left and below (the Khanty-Mansi Autonomous Okrug and the Sakhalin Oblast). The Pomorye region is marked in bright red, while the Samara Oblast is marked with a pink circle. It is evident that the entire ellipsoidal cluster can be divided into two subgroups:

⁴⁰ "Digital Russia" Index: Appendix 1. Moscow: SKOLKOVO School of Management. URL: <https://www.skolkovo.ru/researches/index-cifrovaya-rossiya/> (accessed 31 July 2025).

⁴¹ Created by the author based on the statistical compilation "Regions of Russia: Socio-Economic Indicators" and materials from the website of the Federal State Statistics Service of the Russian Federation (Rosstat). URL: <https://rosstat.gov.ru/> (accessed 11 August 2025).

12 points situated to the right and above that small circle, and all the remaining points are located to the left and/or below. The points for the following regions lie between and near the points of these two areas: several areas within the CFD, the Moscow, Tyumen, and Chelyabinsk Oblasts, the Republic of Udmurtia, and Primorskiy Krai. Pomorye's position according to these two measures of development in "ICT and communications" was fairly good compared with a large number of Russian regions in 2022.

Nevertheless, it is worth noting that among the 12 regions in the ICT-leading subgroup, there are many that fall into Group 1, the strongest in terms of innovation potential (Nureev, Simakovskiy, 2017). Moreover, according to another innovation ranking for 2018–2019, the majority of these regions were included in the list of the country's 14 leaders (Abashkin, Abdrakhmanova, Bredikhin et al., 2021). The locations of some of these innovative regions are situated close to the pink circle in Fig. 5. Based on this observation, if we take 11 regions from this subgroup (excluding the Kaliningrad Oblast), calculate the average level of innovation activity for 2006–2023⁴², and finally take the average values for each of the three years, we obtain the graph shown in Fig. 6).

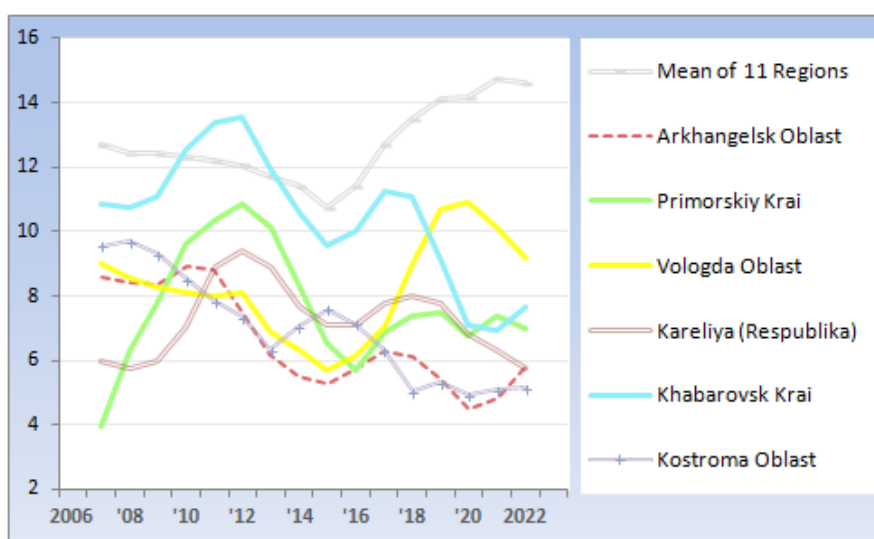


Fig. 6. Level of innovation activity of organizations: dynamics in a number of regions, %⁴³.

It should be noted that this indicator was informative and had previously been included in the list of model factors from the study (Stepanov, Bobkov, Shamaeva et al., 2022). Here, for comparison, the average values—calculated using a 3-year moving window—are shown for several additional regions: Pomorye, Primorye; the Vologda and Kostroma Oblasts; the Republic of Karelia and the Khabarovsk Krai. In terms of a number of its characteristics, Pomorye is similar to these Russian territories. These graphs show that, since 2012, organizations in Pomorye have begun to lag behind those in other regions shown in Fig. 6 in terms of their level of innovation

⁴² Materials from the website of the Federal State Statistics Service of the Russian Federation (Rosstat). URL: <https://rosstat.gov.ru/> (accessed 11 August 2025).

⁴³ Created by the author based on the statistical compilation "Regions of Russia: Socio-Economic Indicators" and materials from the website of the Federal State Statistics Service of the Russian Federation (Rosstat). URL: <https://rosstat.gov.ru/> (accessed 11 August 2025).

activity. It can also be observed that the sharp decline in the level of innovation in the Khabarovsk Krai after 2015 had a negative impact on the dynamics of the Krai's $Y^{(t)}$ estimate in Fig. 1. Thus, between 2015 and 2018, the curve for $Y^{(t)}$ in this region ran close to that of Pomorye; however, between 2020 and 2023, the Khabarovsk curve for $Y^{(t)}$ shifted significantly lower, closer to the curve for Tomsk.

When approaching the red point representing Pomorye in Fig. 5 and moving downwards along the major axis of the ellipse, points representing regions from Group 2, which lags slightly behind Group 1 in terms of innovation, appear more frequently. These included four regions from the CFD, five regions from the VFD, the Tyumen and Omsk Oblasts, the Khabarovsk Krai, and others. Regions such as Pomorye, the Krasnoyarsk and Primorskiy Krai, the Republic of Bashkortostan, and the Leningrad, Magadan, Murmansk and Tver Oblasts belonged to the weaker Group 3. They required relatively high financial investment and the development of specific government support measures to foster innovation (for the period 2011–2016). Furthermore, the Tomsk and Vologda Oblasts were included in the leading ICT sub-group comprising 12 regions; both of them outperformed Pomorye in terms of the ICT index in 2017 and 2018. The Tomsk Oblast belongs to Group 1 (Nureyev, Simakovskiy, 2017), whereas the Vologda Oblast — to Group 2. When interpreting the data presented above for the Tomsk Oblast (as well as the data in Figures 1–6), it is worth mentioning that this region was a consistent leader in the HSE ranking from 2015 to 2018, according to their report (Abashkin, Abdrakhmanova, Bredikhin et al., 2021). It also holds 4th place in the SMART ranking, while Pomorye is in Group D, ranking only 70th⁴⁴.

To raise the level of innovation in organizations in Pomorye, the findings from the article (Toomsalu, Tolmacheva, Vlasov et al., 2019) could be useful; that study analyzes the determinants of innovation in small and medium-sized enterprises, drawing on data from 776 observations, including from EU countries. It is found out that stronger competition, investment in technology, and optimization of business processes at enterprises foster innovation. Conversely, outdated or obsolete equipment, a passive workforce that makes little effort to improve skills and overall level of knowledge, and financial and administrative barriers hinder innovation to varying degrees.

Let us now discuss the similarities in the dynamics of the $Y^{(t)}$ variable (i.e., the estimated value of the II WBP index) shown in Fig. 1. In the case of the Pomorye–Primorye pair, this can be explained by the fact that their GRP structures are similar (Table 4); the values for a number of indicators—GRP, ICT and the digitisation of the economy—were also close in these regions.

Table 4

*Sectoral structure of GRP: contributions of 8 regions in 2019 (%)*⁴⁵

Region	Sequence number of the economic activity sector													
	1	2	3	4	5	6	7	8	9	10	11	12	13	14
														Density

⁴⁴ 2022 SMART Regions Rating. Association of Innovative Regions. URL: <https://i-regions.org/> (accessed 15 August 2025).

⁴⁵ Based on Table 9.4 from the statistical compilation “Regions of Russia: Socio-Economic Indicators”. Materials from the website of the Federal State Statistics Service of the Russian Federation (Rosstat). URL: <https://rosstat.gov.ru/> (accessed 11 August 2025).

Leningrad Oblast (22)	4.4	0.6	28.9	6.7	9.1	9.7	13.6	0.7	9.2	2.5	5.9	2.1	3.6	3	22.4
Khabarovsk Krai (25)	5.8	6.0	9.4	2.7	5.6	15.0	15.0	2.4	8.7	1.7	12.2	4.2	5.2	2	1.7
Tomsk Oblast (30)	3.2	27.5	10.1	2.3	4.8	8.0	8.3	1.9	9.7	4.4	8.8	3.9	4.3	1	3.4
Primorskiy Krai (32)	7.3	1	9.2	2.2	4.4	15.9	18.3	2.0	11.3	2.5	14.2	3.2	4.7	3	11.5
Arkhangelsk Oblast (33)	5.5	4.4	24.5	2.6	4.4	9.2	11.4	1.4	10.5	1.2	10.7	3.9	6.6	3	2.7
Vologda Oblast (34)	3.9	0.0	38.4	2.3	6.3	11.2	10.8	1.7	7.5	2	6.6	2.3	4.0	4	8.0
Republic of Karelia (31)	5.4	18.8	18.4	2.6	3.4	6.0	9.4	1.6	8.2	2	11.2	3.9	6.2	4	3.4
Kostroma Oblast (69)	6.7	0.1	22.9	8.2	4.4	12.5	6.4	2.4	10.1	1.6	10.6	4.7	5.4	4	10.5

Note: A) 1 — agriculture, forestry, and fisheries sector; 2 — extractive industry; 3 — manufacturing industry; 4 — energy sector; 5 — construction; 6 — trade sector; 7 — transport; 8 — ICT and communications sector; 9 — real estate and leasing; 10 — scientific and technical activities, etc.; 11 — services and security; 12 — education; 13 — healthcare and social services; B) column 14 — innovation potential group from (Toomsalu, Tolmacheva, Vlasov et al., 2019); 15 — population density (as of January 1, 2020); C) column 1 — the region's rank by per capita GRP in 2019 (in parentheses).

Although both regions were classified in the weaker Group 3 in terms of innovation potential (Nureev, Simakovskiy, 2017), Primorye has outperformed Pomorye in terms of innovation activity since 2010 (Fig. 6). Apparently, this is due to the fact that the structure of processing industries in Primorye is heavily dominated by the machinery sector 9 (Table 5), as well as sectors 6 and 8.

Table 5

Structure of “goods, works, and services shipped” in the PI sector (%), 2019⁴⁶

Regions	1	2	3	4	5	6	7	8	9	10	11
Arkhangelsk Oblast	6.3	20	44.3		2.4		3.8		14.6		5.4
Vologda Oblast	7.7	5.4			19.4	2.0	58.4				
Leningrad Oblast	19.5	2.6	9.7	28.4	8.1	5.7	4.7	3.9	14.1	2.3	
Republic of Karelia	12.7	16.6	47.5		2.7	2.7	6.3		3.4		6.7
Kostroma Oblast	8.6	21.9		4.5	3.7	2.1	18.9		13.8	21	
Primorskiy Krai	20.2	4.2				5.5	2.8	1.8	46.4	3.6	10.8
Tomsk Oblast	18.5	8.7	2.6	19.3	15.1	3.0	6.5	18.3	2.5		4.4
Khabarovsk Krai	11.5	3.8		15.9		2.8	36.8		23.5		3.8

Note: A) 1 — food production; 2 — wood processing (PI); 3 — pulp and paper production; 4 — petroleum/coke/rubber/plastics production; 5 — medical/chemical production; 6 — non-metallic mineral manufacturing; 7 — metallurgy; 8 — electronics/electrical equipment manufacturing; 9 — machinery/equipment manufacturing; 10 — furniture and other product manufacturing; 11 — repair and installation of machinery/equipment. B) If the contribution was below 1.8%, it was not shown in the table (for simplicity).

The same can be said, more or less, when comparing data from the Kostroma Oblast with similar data from Karelia. It is also evident from the rows in Table 5 that the economic sector structures in Pomorye, the Kostroma Oblast, and the Republic of Karelia are similar. In these three regions, the share of Sector 4 (manufacture of petroleum products, coke, rubber and plastic products) is very small. Along with other factors, this likely contributes to the fact that the graphs of the variable $Y^{(t)}$ in Fig. 1 exhibit similar dynamics, differing only by a shift along the y-axis. However, due to better dynamics of the RFID (Fig. 3) and slightly better LE dynamics (Fig. 4),

⁴⁶ Based on Table 13.5 from the statistical compilation “Regions of Russia: Socio-Economic Indicators”. Materials from the website of the Federal State Statistics Service of the Russian Federation (Rosstat). URL: <https://rosstat.gov.ru/> (accessed 11 August 2025).

higher ranking in terms of the CDI in 2017–2018, and even stronger innovation potential (Table 4, column 14), the Pomorye region slightly increased its lead over the two aforementioned regions following the pandemic.

Furthermore, it is important to note that variable X_5 , relating to subsidies, requires correct interpretation. A reduction in the budget transfer payments (BT) in the regional budget does not directly lead to an increase in the II WBP indicator. This means that if the socio-economic situation in a region improves, leading its authorities to borrow less from the federal treasury, the BT will decrease, while the aggregate II WBP indicator will subsequently tend to rise slightly.

As regards the appropriateness of using Model 1, which was constructed using panel data from the CFD, in relation to territories within or near the AZRF, this issue requires specific investigation. It would appear be more appropriate to select a set of AZRF regions and/or neighboring ones (both fully and partially included in AZRF), compile a panel dataset covering the periods 2015–2019 and 2022–2025, and then calculate the actual Y values based on the methodology described above and in existing publications (Stepanov, Bobkov, Shamaeva et al., 2022; Aivazian, 2012; Stepanov, 2022; Stepanov, 2019). Subsequently, a panel regression model could be constructed using the calculated Y values and data collected for potential explanatory variables. Examining international experience would also be highly beneficial in this regard.

Briefly addressing aspects related to LE, the following points can be noted. The life expectancy at birth indicator is frequently used in comparisons between countries (Shtun, 2021) or Russian regions (Stepanov, 2024; Rodionova, Kopnova, 2020; Blinova, Bylina, Rusanovskiy, 2020; Lopaeva, Lopaeva, 2022), as well as in statistical modeling. Furthermore, this indicator is a key component of the human capital development index, which is widely used to compare countries or Russian regions. In practice, LE is calculated using mortality tables based on data on the number and age of deceased individuals obtained from civil registry offices; it also serves as an indicator of the population's health status. LE also serves as one of the measures of the socio-economic living conditions of the population (Shtun, 2021). The following factors are frequently used in life expectancy models: the Gini index of social inequality; the proportion of residents with access to safe drinking water; alcohol consumption among adults (adjusted to 95°); other alcohol-related factors; cigarette smoking; CO₂ emissions; various indices of residents' educational attainment, and many others (Stepanov, 2024; Shtun, 2021; Amos, Smirnov, 2022; Vladimirskaia, Kolosnitsyna, 2023; Perova, Korchemny, 2021; Rodionova, Kopnova, 2020; Blinova, Bylina, Rusanovskiy, 2020).

The study (Lopaeva, Lopaeva, 2022) concludes that, across the world, “mortality depends primarily on living conditions and circumstances that are mainly caused by ... conflicts and a low level of social responsibility on the part of the state”. It also presents the contributions of various factor groups to life expectancy, based on WHO estimates and the opinion of Prof. G.E. Ulumbekova.

Western researchers have demonstrated the positive impact of implementing a set of

measures aimed at increasing life expectancy in a given area (Nguyen, Li, Wang et al., 2023). These measures include complete smoking cessation, minimal and infrequent alcohol consumption, adequate physical activity, stress reduction, balanced diet, and others. Their implementation can significantly increase life expectancy regardless of citizens' gender, ethnicity, or various other factors. It is worth noting that the issue of reducing tobacco consumption is particularly relevant for the population of the AZRF regions listed in the table in (Kuratova, 2023). For instance, the prevalence of smoking among adult residents, with the exception of three high-income autonomous okrugs, was above the average level; another exception is Karelia, where this figure was equal to the Russian average for the first half of 2025⁴⁷.

A group of researchers, primarily from Harvard University, had previously conducted an in-depth study on the impact of five lifestyle factors on the risk of premature mortality and life expectancy, using the average US resident aged 50 or older as a model, and presented their findings in (Li, Pan, Wang et al., 2018). The study examined deaths from all causes as well as those resulting from major chronic non-communicable diseases. Based on data from over half a million people across 17 countries, it was determined that approximately 60% of premature deaths could be attributed to five unhealthy lifestyle indicators: cigarette smoking, excessive alcohol consumption, physical inactivity, unbalanced diet, and obesity. Statistics were also compiled over a 40-year period based on data from approximately 79,000 American nurses (at the turn of the 20th and 21st centuries), and, slightly later, for approximately 44,000 healthcare professionals of both sexes, similarly over a 30-year period. For each observation, five levels of variation for each factor were recorded; for example, regarding smoking: "never smoked", "used to smoke but has given up", "1–14 cigarettes per day", "15–24 cigarettes per day", and "25 or more cigarettes per day". Reference values representing the lowest mortality risk were then selected for these factors: "never smoked", "5–15 g of alcohol per day", "at least 3.5 hours of physical activity per week" at the required intensity, a body mass index of "23–25" (kg/m²), and an "optimal" diet quality index. Additionally, a composite healthy lifestyle score, ranging from 0 to 5, was obtained for each subject from a US national database. The authors then analyzed approximately 42,000 deaths within this population over 34 years of observations from the official WONDER database and calculated life expectancy figures. Using the powerful SAS statistical software package and the Cox's proportional hazards model, they estimated hazard ratios and constructed 95% confidence intervals for the variables under consideration. They present several tables and graphs illustrating how various combinations of the five aforementioned factors influence the risk of premature mortality for the average US citizen aged 50 or older. This analysis was conducted for three scenarios: all-cause mortality, mortality from cancer, and mortality from cardiovascular disease. Thus, if the patient is a 50-year-old American woman and all these factors are at their reference values, she can, on average, gain 14 years of life due to this lifestyle, with a 95% confidence

⁴⁷ Interdepartmental Information and Statistical System (EMISS): Prevalence of tobacco smoking among the population aged 15 and older. URL: <https://fedstat.ru/indicator/63004> (accessed 18 August 2025).

interval (11.8; 16.2), compared with another average US resident for whom each of the five factors was at its worst level. The study also provides very useful graphs for each gender, showing the average reduction in life expectancy (starting at age 50) associated with an unhealthy lifestyle (based on variables such as daily cigarette consumption, weekly alcohol intake, physical activity levels, etc.). It is clear that, with minor adjustments, these results would be useful in developing preventive measures in the regions of the AZRF and many other territories.

Conclusion

The Arkhangelsk Oblast, which is partially included in the AZRF, was selected as the object of the study.

The methodological basis of the study was the application of algorithms drawn from two branches of statistics: principal component analysis and correlation-regression analysis. These algorithms were applied to panel data compiled for regions in Central Russia and the Volga region. Additionally, the study employed the quality-of-life analysis methodology outlined in S.A. Aivazian's monograph (2012), in particular when constructing an aggregated variable serving as a measure of the population's well-being. Two regression models were applied to multi-year statistical data from Pomorye and several other regions, and the results obtained are clearly illustrated.

An attempt has been made to justify the selection of the regions used for benchmarking the indicators from Pomorye. An illustrative example is also presented, demonstrating measures that could improve the aggregated welfare indicator for 2020, as well as life expectancy of the population of Pomorye in 2019. The discussion includes a brief overview of works regarding the development of transport infrastructure and information technologies in several regions of the AZRF, as well as research on life expectancy and its modeling. Attention is also focused on innovative aspects of development and on the progress made by Western scientists towards increasing life expectancy.

For the first time, the specification of Model 1, which was applied to data from the Pomorye region, is presented, and the dynamics of its key factor variables are analyzed. These variables include an infrastructure metric, several indicators of organizational digitalization, a human capital indicator (specifically life expectancy), and others. Examining the dynamics of these factor and aggregate variables revealed a number of problem areas in Pomorye across several dimensions. Some of these issues are clearly illustrated in charts and graphs and compared with 7–8 regions that share similar characteristics with Pomorye. Another novel aspect is that a statistical relationship has been formally established between road and transport infrastructure variables, as well as indicators of the digitalization of organizations' activities and an aggregated variable for well-being. In addition, a new regression model for life expectancy was applied to the data described above for the first time. Both models made it possible to identify the factor variables with the strongest influence.

The data analysis methodology may also be of independent interest, as it can be applied to other regions within the AZRF and/or neighboring regions, as well as to other regions selected from various districts across the country. A number of parallels identified during the analysis of the socio-economic development of the regions may also be of interest. The findings of the study may be useful to the authorities responsible for managing the regional development of the AZRF territories and other regions of Russia when formulating measures to implement their strategic programs.

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