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Article

A methodological approach to complex territorial development based on agglomeration effects: "Smart" specialization perspective

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Abstract: Regional differentiation in the Russian Federation is considered to be high in terms of gross regional product (GRP) per capita level, growth rate, and other indicators. Inefficient use of region-specific spaces entails redistribution processes in order to maximize positive agglomeration effects throughout the country. These encompass economic restructuring based on production value-added chain extension and expanding inter-regional collaborative linkages. Besides, it is vital to assess the opportunities of individual Russian territories for participation therein. The research goal is to develop a scientifically based methodology to determine promising sectoral composition of the regional economies and that of spatial interactions. Such methodology would consider the feasibility of combining "smart" industrial specializations, regional resource potential, prevailing contradictions in the economic, innovative, and technological development of the country's internal space. The proposed methodological approach opens the way to exploit the existing regional economic potential to the full, firstly, via establishing sectoral priorities of the region regarding the regulatory factors for the territorial capital to have a major effect on the increased potential GRP level; secondly, through benchmarking performance of the available development reserves within leading regions from homogeneous groups having similar characteristics and factor potentials; thirdly, via developing inter-regional integration prospects in terms of regional potential redistribution to ensure growth in potential gross domestic product. An extensive analytical and applied investigation of the proposed methodological approach was carried out from 2014 to 2020. Diversified estimates were obtained for a wide range of indicators due to evidences from 85 Russian regions and 13 types of economic activity. Such an integrated approach allows revealing actual imbalances and barriers that impede regional development, ensures the efficient use of production factors, and enables to trace ways to implement transformation policies and design effective regulatory mechanisms. The results provide arguments in favor of strengthening inter-regional connectivity and supporting inter-regional cooperation. This insight not only contributes to the academic discourse on complex development of a territory but also holds practical implications for policymakers and regional planners aimed at ensuring comprehensiveness and robustness of the evaluation supporting the decision-making process.

Keywords: clustering; region; spatial development; industrial concentration; methodological approach; agglomeration effects; smart specialization

1. Introduction

Russian regions are characterized by various natural resources and key socio-economic, administrative, financial, socio-cultural, climatic, etc. features (Artemova and Uzhegov, 2021) to create the preconditions for the concentration of certain industries therein. One should detect and apply such tendency on a systematic basis, since the geographic localization of industries advances the manifestation of agglomeration forces in the economy and can provide a significant contribution to the economic growth of the constituent entities of the Russian Federation and the country as a whole (Spatial Development Strategy, 2019). In terms of managing the economic space, in our view, such "compression" would allow focusing government support measures and increasing budgetary and socio-economic efficiency thereof.

Professor Alexander A. Shirov made a report in the context of scientific and technological development agenda at the V Moscow Academic Economic Forum (MAEF, 2023). In his speech, the academician analyzed the prospects for implementing a structural and technological maneuver in the current realities. Taking into account the emerging trends, and based on the calculations, it was shown that the task of the medium-term Russian economic policy should be realizing the economic growth potential of 4-5% premised on its structural transformation. Solving this problem would require increasing the volume of research and development (R&D) investment, going through the stage of economic complexity based on extension of production value added chains and expanding cooperative cross-sectoral linkages.

It should be noted that numerous attempts by decision-makers on economic modernization to transform the system of economic relations in order to ensure its qualitative growth and stimulate regional development factors have not yet been successful. A recent attempt to predict a long-term structure of the regional economy presented in 2019 in the Spatial Development Strategy of the Russian Federation for the period up to 2025 sparked an active debate. Many scientists expressed sharp criticism in terms of correctness and scientific validity of provisions contained in this document (Demyanenko, 2020; Ivanov and Buchvald, 2021; Kvint, 2019; Kuznetsova, 2019; Minakir, 2018).

A scientific search initiated back in 2019 led to the conclusion that the most promising tools for selecting a list of priority industries should include smart specialization strategies. Based on a previously conducted bibliometric analysis of the literature (Gamidullaeva, 2024), we believe that the concept of smart specialization is aimed at developing interaction between regions through the consolidation of their resources and joint development of innovative products. It would lead to the creation of synergy and complementarity, capacity-building to work at inter-sectoral and inter-regional levels, and, ultimately, to long-term economic growth.

However, there is neither consensus regarding the most effective approaches to identifying promising specializations and, accordingly, the prerequisites for the formation of industry clusters, identifying and assessing the agglomeration processes therein, and the effects on the regional economy in modern domestic science. According to A. Kotov, an attempt to present a unified methodology for identifying smart regional specialization is generally limited to an array of data to form the basis for the subsequent process of searching for smart specializations (Kotov, 2020). A solution to this issue would allow building a unified approach to the implementation of an effective model of spatial policy in Russia, which would link the priorities of the economic structure with state support tools in the form of clusters, special economic zones, etc.

Nevertheless, there are numerous academic studies that substantiate the viewpoint regarding most of the existing industry clusters in Russia. Since they do not create positive agglomeration effects for the region and the country, these are not claimed to be as such (Degtyarev, 2018; Davankov et al., 2020; Makar and Yarasheva, 2020). In other words, such spatially localized systems only resemble clusters in form, since they have a clearly defined center, attract population and resources from the periphery, etc. These are not such by their nature as they do not lead to increased efficiency in using resources, reducing losses and, in general, increasing productivity. It is also worth noting that the work of agglomeration effects is not often obvious, which requires a more thorough analysis and development of appropriate methodological approaches (Kolomak and Sherubneva, 2023). Our understanding of the category "cluster" and "industrial cluster" as an integrated approach to territorial development is presented in previous studies (Gamidullaeva et al., 2022b; Gamidullaeva, 2023).

The academicians at the Institute of Economics and Industrial Engineering of the Siberian Branch of the Russian Academy of Sciences (IEIE SB RAS) emphasize that the rationale for economic specializations that are promising for the region should be based on its competitive advantages (Kolomak et al., 2018). However, it is also vital to determine the presence of additional factors that contribute to the spread of both regional and sectoral agglomeration effects from the concentration of certain types of economic activities in the region. This will provide an understanding of the current set of conditions for transforming the economy and stimulating growth. The absence of such effects is a serious obstacle to territorial development, as it leads to a decrease in the investment attractiveness of a territory, and a reduction in the efficiency of potential infrastructure and production project implementation.

The above stated raises many questions regarding ways to achieve concentration (localization) either through spatial placement or via increasing transport accessibility and availability. These issues also concern the importance of inter-regional interaction between subjects, density and quality of basic infrastructures, the effective use of factor potential (capital, labor, innovation and technological and other factors), formation and assessment of various direct, indirect and induced external effects.

An increased level of sectoral concentration in the regional economy indicates a predisposition to certain specializations and is only one of many prerequisites for the emergence of agglomeration effects. In our opinion, regions should anyway have a specialization related to historical experience, geographical and climatic (e.g., access to the sea, administrative and territorial boundaries, etc.), and financial features (Gamidullaeva et al., 2022a).

It is essential to take into account that transport accessibility, infrastructure provision, institutional development, etc. are important factors being accompanying ones that maximize regional and sectoral agglomeration effects, indicating the optimality of the existing sectoral proportions.

In our opinion, it is advisable to study agglomeration effects at the level of regions that gain agglomeration effects from the concentration of certain industries and regional specialization therein. These effects have a fairly wide range: from external direct and indirect effects (economies of scale, the possibility of sharing factors of production, reduction of transaction costs, inter-sectoral effects, and other economic opportunities) to induced ones resulting from inter-regional spillover effects when costs are borne by some regions, while others are also beneficiaries.

As is known, the terms "cluster", "localization", and "sectoral (industry) concentration" are used along with the definition of "sectoral (industry) agglomeration" in the literature. An agglomeration (from Latin *agglomeration*—accumulation, conglomeration") is a concentration or grouping of settlements united in a complex territorial system based on diverse chain communications (social, labor, production, investment, recreational, cultural, etc.), as well as sharing of various resources of this location in order to improve the unified socio-economic space of the region. Thus, agglomeration effects created by industry agglomerations should be understood as concentration effects, and those created by regional agglomerations should be understood as specialization or diversification effects. The region in this context is a kind of inter-sectoral cluster.

The aim of this research is to develop and test a scientifically based methodology for determining the promising industry structure and priority directions for the development of regional economies to maximize positive agglomeration effects, taking into account socio-economic, innovative, technological and other characteristics of the region. Such an integrated approach would facilitate the involvement of the existing potential through the identification and use of intra-regional reserves, building effective inter-regional interaction that creates economic effects via coordinated economic policies all over the country.

2. Literature review

Currently, the issues regarding spatial transformation and development of territories, formation and implementation peculiarities of state regional policy are the spotlight for leading domestic and foreign scholars (Allen and Arkolakis, 2018; Bukhvald, 2018; Desmet and Rossi-Hansberg, 2014; Kuznetsov et al., 2019; Kuznetsova, 2019; Martin, 2005; Minakir, 2015, 2019; Yilmaz and Sensoy, 2023). The concept of regional smart specialization is among widely debated approaches. Thus, the Spatial Development Strategy of the Russian Federation for the period until 2025 highlights the postulate of regional smart specializations. Unique competencies of the regional economy (Barca et al., 2012), high validity and evidence through quantitative indicators and an extensive empirical base (Kroll et al., 2014), and inter-sectoral and inter-regional nature should be regarded as the key features of smart specialization strategies. However, lacking unified socio-economic grounds for the effective implementation of identical mechanisms to determine promising regional specializations is a challenging issue.

Various indicators and calculation methods are applied in international and Russian practices to identify current specialization of regions, and the localization coefficient, also known as the Hoover specialization index being the most popular one. The Gini concentration index, the Krugman and Hallett specialization indices, the Lilien index, the Ellison–Glaeser index (EGI), etc. are used for identifying sectoral diversity and geographic distribution of industries in regions. Mainstream techniques for identifying regional specialization industries include various coefficients, such as inter-district marketability, per capita production, the Herfindahl–Hirschman index (HHI), and the localization coefficient (Kutsenko and Eferin, 2019).

Numerous approaches are used to investigate promising economic specializations of territories within the framework of the smart specialization theory, the economic complexity theory (Moiseev and Bondarenko, 2020), and the concept of technological proximity (Rastvortseva and Amanalieva, 2021). One should mention an approach to assessing sectoral and regional fragmentation of production, agent-oriented and cross-industry modeling of value-added chains (Lukin, 2019; Lukin et al., 2020). Lukin (2023) offers an approach to searching for prospective specialization of regions in the North-West of Russia based on the average position thereof in the value-added chains. Diverse methods are used to select and justify a promising market niche for the region, e.g., mapping the technological landscape (Paap, 2020), modern scientific literature overview on potential product niches, etc.

Thus, Berchenko and Mishin (2018) presented a methodology based on a step-by-step algorithm for identifying promising foreign economic activities (FEA) that concentrate the key regional resources and competencies for further thorough expert study to assess the future development prospects. It is noteworthy that the “stage of industry development” indicator (birth, maturity, growth, development, and decline) is used along with the criteria for assessing the development potential of specialization areas. Then, the rating scores for types of economic activities were formed based on a number of criteria (prospects for specialization areas; investment attractiveness; clustering potential; availability of human resources; level of innovation).

Zyuzin et al. (2020) analyzed a large volume of cross-sectional 2017 data for nearly 650,000 individual (micro, small, medium, and large) enterprises. The authors view the possibility of bias in estimates due to the preservation of both significant and insignificant factors in regression models.

Rumyantsev et al. (2022) considered data from the regional input-output table to take into account the level of technological complexity expressed in the number of processing stages in the process of obtaining an industrial product and in the process of transforming an industrial goods into a final demand goods. Unfortunately, regional input-output tables have not been calculated by Federal State Statistics Service (Rosstat) since 2016. Though such data are not presented officially, these are accumulated as part of investigations conducted by some research institutes (e.g., Vologda Research Center of the Russian Academy of Sciences, IEIE SB RAS, Economic Research Institute of Far Eastern Branch of the Russian Academy of Sciences).

The methodology proposed by Kutsenko and Eferin (2019) is based on the approaches of the European Cluster Observatory to identify industries of specialization and assess the potential for the further development thereof using a scoring method based on four indicators (level of specialization, size, productivity, and dynamics). The advantage of this approach is that the identified list of specializations in the region is subject to the restriction of classifying the territory in the top 80% of regions in size and the presence of a “star” in terms of specialization.

The methodological approach introduced by Kotov et al. (2019) is based on the construction of regional competency matrix. The authors calculated a number of indicators to assess the effectiveness of current industry specialization, innovation potential and patent and publication coverage in the context of wide range of economic activities. The advantages of this methodological approach include a detailed industrial nomenclature of the study, accessibility and ease of interpretation of the used statistical data, and comprehensiveness of regional competency analysis.

Lebedev et al. (2022) presented an approach that harmonizes regional sectoral specialization with the structure of training of higher education specialists. The methodology involves assessing the localization of economic activity types and employment of the population. A correlation of graduates in the context of enlarged groups of specialties and areas with the structure of population employment allows developing recommendations for adjusting the educational policy of regional universities.

A novel method to check starting points for smart specialization process that should be implemented to avoid errors in decision making process is proposed by Kranjac et al. (2018).

Orlova and Yan (2024) put forward a conceptual approach to establishing industry priorities for the implementation of "smart specialization" projects in a region with the highest investment potential level. The proposed management matrix to simulate the prospects for regional sustainable innovative development allows justifying promising areas of "smart specialization".

Some authors focus on specific industries, considering, for example, the issue of choosing a model of agricultural specialization for the regions of Siberia in the context of "smart specialization" (Aleschenko and Aleschenko, 2020).

Kolmakov et al. (2019) propose an assessment of regional industrial specialization to measure both the industry's contribution to the competitiveness of the region and the closeness of competitive ties between regions. It would help identifying industries that can generate a positive effect from the use of competitive specialization territories.

Dubrovskaya et al. (2018) provide a rationale for the feasibility of using regional benchmarking in accordance with smart specialization principles as an effective tool for territorial innovative development.

The disadvantages of the considered methods include poor elaboration of inter-regional and spatial interaction issues, which is mainly associated with the possibilities of information support for the analysis and assessment of promising specialization. The authors often use an expert approach to assessing a number of key parameters, which, as is known, is subjective in nature.

Despite the growing body of related literature, there is a need for more comprehensive studies. In our opinion, it is urgent to develop a holistic scientifically based approach, taking into account the existing contradictions and imbalances in the economic, innovative, and technological development of the economic space. An original approach would focus on maximizing positive agglomeration effects from the spatial distribution of industries by connecting thereof with the potentials of regional economic spaces and the advantages of inter-regional relationship. The present study aims to bridge this gap, having provided a methodological approach to complex territorial development.

3. Methodology

The conducted research process has undergone several stages (**Figure 1**).

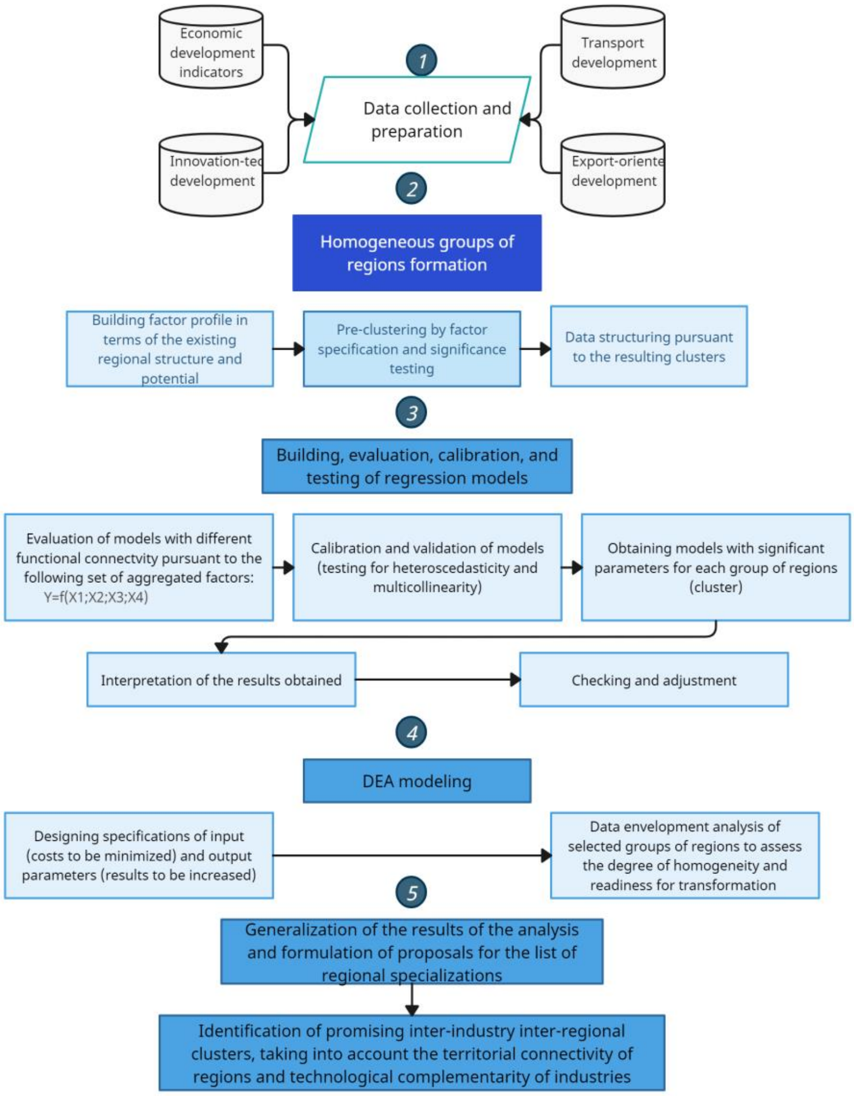

Figure 1. Research methodology flowchart.

The first stage was data collection and preparation. Data set on regional economic and technological development, transport accessibility, and export activities involved some limitations. Apart from problems concerned with the quality of regional statistics (comparability, data omissions, delays), the greatest difficulties were caused by evaluating the two aspects. The first one was an assessment of sectoral technological development level in a region to justify the feasibility and planning of inter-regional interactions in terms of sectoral technological maturity. Another important aspect was consideration of regional spatial relationships to plan inter-regional interactions in terms of territorial connectivity.

At the second stage, homogeneous groups of regions were formed. This stage was very important, as it provided for territorial characteristics when developing management impacts. In fact, the same mechanisms for stimulating development in different regions could lead to various consequences and socio-economic effects.

Thus, the regions were divided into groups (clustered) in accordance with 27 out of 69 selected and verified indicators. The clustering employment parameters enabled us to ground sectoral structure proportions. Accordingly, this made it possible to carry out correct modeling of the relationship between gross regional product (GRP) per capita and other parameters based on regression testing tools at the next stage.

Eight clusters were obtained based on the performed calculations. There were both single-region and multi-region clusters, consisting of 39 regions. Significant differences between the clusters were confirmed by Ward's method and a dendrogram constructed using the Euclidean distance. The key features of the identified clusters were described and typical regions in each cluster were determined.

Preliminary findings on the manifestation of concentration effects in the studied regional clusters and predisposition thereof to certain specialization sectors were made by calculating HHI for regional economic concentration and EGI for localization of economic activities.

The third stage involved building, evaluation, calibration, and testing of regression models.

Data from 2020 were used for regression modeling. Spatial data models were used for clusters with multi-scale observations (Clusters 5, 6, and 7). Dynamic models were used for single-region clusters (Moscow, Cluster 1 and Khanty–Mansi Autonomous Okrug—Yugra, Cluster 4), where relationships were simulated using data from 2014–2020. Panel models with spatial fixed effects were used for clusters with two and four regions (Clusters 2, 3, and 8).

As a result, significant factors (predictors) influencing the dynamics of GRP per capita in the region were identified for each identified cluster.

This stage involved evaluation, calibration, and testing of the resulting models for heteroscedasticity and multicollinearity. Further, the interpretation of the obtained modeling results was carried out in order to describe the selected clusters (groups of regions), to determine their industrial potential and the key features of socio-economic, innovation, and technological processes occurring therein for subsequent development of effective directions to stimulate growth and increase agglomeration effects from the concentration of individual regional sectors in the cluster.

The student's *t*-test (*t*-statistic) was used to assess parameter significance of the regression equation. The criteria calculated in the model should exceed the table value for the number of degrees of freedom $df = n - m - 1$, where n is the number of observations, m is the number of factors (regressors) in the model at a given probability $\gamma = 0.95$. This parameter is expressed as the error probability value (Prob.), indicating the probability of the difference between a true free parameter value in the model and the value found by the least squares. The explanatory power of the model is expressed by the adjusted coefficient of determination (Adjusted R-squared). It indicates the variation percentage of the explanatory variable (GRP_pc), expressed by the variation of the independent variables taken as regressors. Statistical reliability of equations was estimated using the F-test (F-statistic). If it exceeds the table value for a given number of factors (m) and number of degrees of freedom (df), then the equation is statistically reliable and significant.

Special tests were also used for: 1) multicollinearity of model factors (correlation matrix; assessment of the variance inflation factor; assessment of χ^2 criterion using the Farrar–Glauber test); 2) heteroscedasticity of the model (assessment of the Goldfeld–Quandt test and the White test); 3) autocorrelation of residuals (the Durbin–Watson statistic). All models presented below have undergone special tests to confirm quality and acceptable explanatory power thereof.

At the fourth stage, data envelopment analysis (DEA) was carried out to optimize the development trajectory of regional socio-economic systems. We tested three data sets and, accordingly, obtained three DEA models, varying in the average efficiency assessment.

Benchmark-based analysis of the resulting models allowed determining the best experience of regions that have optimal structural proportions and an optimal development trajectory within each cluster. It seemed essential to carry out proportional and/or transformational changes in the economy structure with DEA tools for groups of regions. Transformational changes indicate regional demand to reconsider sectoral structure and that of economic relations to achieve optimal proportions via, for example, modernization, clustering policies, and increasing external agglomeration effects.

Several sets of factors were tested as part of the optimization modeling using DEA tools:

1) A set of data based on the structure obtained at the previous stages of high-quality and reliable regression models, which involves the assessment of a different set of data for each cluster. The goal was to identify leading regions (a kind of benchmarks for the optimal relationship structure between input and output (GRP per capita) parameters) and to evaluate corrective changes in inputs. In this case, models with constant returns on scale were considered, which became possible due to clustering at the preliminary stage and obtaining eight homogeneous groups of regions;

2) A set of data from the given database, available for all regions in Russia. Since some models are assessed as dynamic ones (for single- or multi-region clusters), and some as spatial ones (for clusters with multi-scale observations), we were limited by data availability for the entire period from 2014 to 2020 in the selection of factors. In the first case, decision-making units (DMUs) were indicators of the region for different years, and in the second case—indicators of various regions. The goal was to assess the degree of optimality of achieving GRP per capita (output) by different regions based on a unified set of factors.

3) A set of data similar to those in item 2, but with a different structure of input and output parameters.

At the fifth stage, the results of the analysis were summarized and proposals for justified regional specializations were formulated. Promising sectoral clusters could be determined taking into account the degree of territorial connectivity of regions. The proposals were formulated to improve the regional development management system for the selected groups of regions to maximize positive agglomeration effects from the concentration of certain types of economic activities therein.

The following grouping of industries was taken as the basis (**Table 1**).

Table 1. Integrated types of economic activities.

Group designation	Name of the integrated group for economic activity types
SH	Agriculture, forestry, hunting, fishing and fish farming
Dob	Mining and quarrying
Obr	Manufacturing industry
Lok	Electricity, gas, steam, and air conditioning supply; water supply and water disposal; organization of waste collection and disposal; pollution-eliminating activities
Str	Construction
Torg	Wholesale and retail trade; repair of vehicles and motorcycles
TrH	Transportation and storage
Gop	Hotel activities and catering services
Inf	Information and communication activities
OpN	Real estate activities
Obr	Education
Sdr	Human health and social care activities
Dr	Other activities

Primary information sources were Rosstat data (specialized collections), Unified Interdepartmental Statistical Information System (UISIS) database, Federal Tax Service, Federal Customs Service, Federal Service for Intellectual Property (Rospatent), etc.

4. Findings

Mathematical clustering was initially used to divide the regions of Russia into more homogeneous groups. For this purpose, pre-clustering was carried out using Ward's method, a clustering dendrogram with confidence levels was constructed, and the number of clusters was determined. Thus, eight clusters are distinguished with a sufficient level of difference. Therefore, further clustering using the k-means method was carried out in order to determine the refined parameters and control the degree of statistical significance between the selected groups according to the clustering parameters using analysis of variance (ANOVA).

Primarily, the analysis included 69 parameters (according to the indicator passport) for an extensive list of socio-economic, innovative, and technological variables. An ultimate specification of 27 clustering parameters was found premised on ANOVA results and exclusion of parameters with neither significant difference between groups of regions. Data on the significance of performed clustering according to used parameters was determined by assessing the level of error probability when dividing into groups. In this case, it did not exceed 5% for all parameters (**Figure 2**).

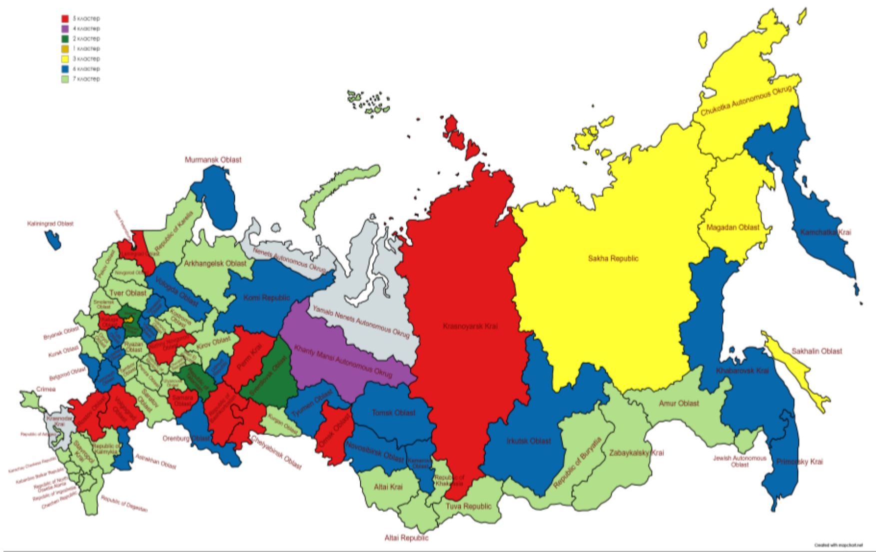

Figure 2. Clustering of regions by key economic features.

Table 2. Typical regions and key features for the eight identified clusters.

Typical regions	Number of incorporated regions	Gross regional product per capita (GRP_pc), thousand rubles	Ratio of fixed capital investments to GRP (Obnov_GRP), percentage	Herfindahl-Hirschman index (HHI)
Moscow (Cluster 1)	1	1555.6	0.160	1597
Average for Cluster 1		-	-	-
St. Petersburg (Cluster 2)	4	950.6	0.099	1334
Average for Cluster 2		731.2	0.137	1461
Chukotka Autonomous Okrug (Cluster 3)	4	1898.6	0.00002	2125
Average for Cluster 3		1769.1	0.007	2922
Khanty-Mansi Autonomous Okrug–Yugra (Cluster 4)	1	2733.6	0.023	5296
Average for Cluster 4		-	-	-
Samara Oblast (Cluster 5)	12	530.6	0.080	1240
Average for Cluster 5		522.3	0.066	1510
Udmurt Republic (Cluster 6)	21	480.0	0.019	1441
Average for Cluster 6		586.4	0.017	1540
Kostroma Oblast (Cluster 7)	40	319.4	0.002	1228
Average for Cluster 7		323.4	0.007	1253
Nenets Autonomous Okrug and Yamalo-Nenets Autonomous Okrug (Cluster 8)	2	-	-	-
Average for Cluster 8		6620.5	0.0002	5794

Table 2 shows that the differences between the clusters are significant. For example, Herfindahl-Hirschman index varies from 1228 to 5794. The distribution of regions according to the degree of economic diversification in accordance with the calculated HHI index is shown in the figure (**Figure 3**).

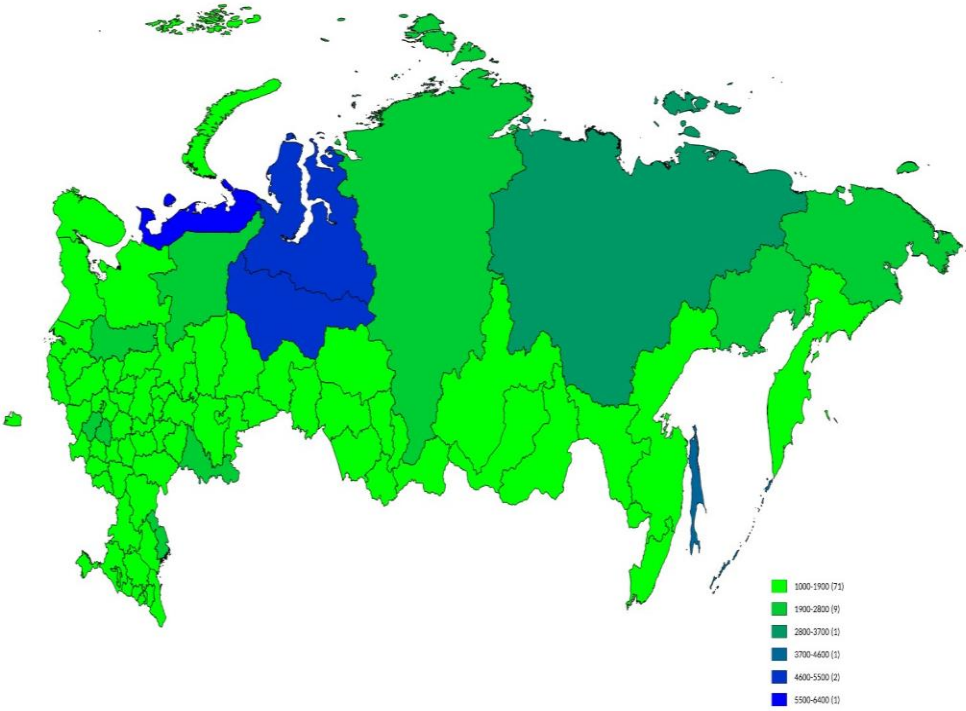

Figure 3. Russian regions' economy diversification.

Moreover, the employment parameters taken into account during clustering made it possible to lay out the proportions of the sectoral structure, and to correctly model the relationship between GRP per capita and other parameters based on regression testing tools (**Table 3**).

Table 3. List of qualitative models obtained for each cluster based on 2020 data.

Cluster No.	Specification	R^2
1	GRP_pc = –10297894.4 + 1029907.0LNZarp + 3727.5Obn_Invest	0.978
2	GRP_pc = –2850518.0 + 313450.1LNZarp + 3779.5High_GRP – 12822.9LNTech_innov + 16442.9Patent – 9058.8Obnov_Reg	0.835
3	GRP_pc = –20811197.0 + 1953234.0LNZarp – 13503.0Inv_GRP – 595125.2Patent + 67301.5Bezrab	0.645
4	GRP_pc = 4831696.7 – 65763.1Inv_GRP – 288565.1Bezrab	0.991
5	GRP_pc = –12367806.3 + 1190216.8LNZarp + 39665.8LNTech_innov(–1) – 6907.0Inv_GRP	0.975
6	GRP_pc = –5628355.5 + 590512.2LNZarp – 6665.9Collab(–1)	0.759
7	GRP_pc = –3258925.8 + 317972.6LNZarp + 45188.0Patent – 6228.9Bezrab + 2645.9Gruz_Rail + 2667.0I_Trud	0.805
8	GRP_pc = 11235106.0 – 25510.2High_GRP – 57546.5Inv_GRP – 152979.4Equip_Reg	0.920

where

Bezrab—unemployment rate;

Collab—enterprises involved in joint R&D ventures;

Equip_Reg—share of fixed capital investments in M&E in the total investment volume in R&M by constituent entities of the Russian Federation;

GRP pc—GRP per capita;

Gruz_Rail—shipment of goods by public rail freight transport;

High_GRP—share of high tech and knowledge-intensive industries in GRP relative to the level of 2011;

Inv_GRP—ratio of gross fixed capital formation to GRP;

I-Trud—labor productivity index in basic non-resource sectors of the economy;

LNTech_Innov—expenses for technological innovations of organizations;

LNZarp—logarithm of average monthly nominal accrued wages;

Obnov_Invest—increase in investment in fixed capital (excluding budgetary funds) compared to the previous period;

Obnov_Reg—share of fixed capital investments in renovation and modernization (R&M) in the total investment volume;

Patent—number of domestic patent applications for inventions filed in Russia per 10 thousand persons.

A list of most and least localized sectors of the economy was compiled according to the analysis results (**Table 4**).

Table 4. Level of economic sector localization.

Types of economic activities	**Ellison-Glaeser index**
Most localized sectors	
Wholesale and retail trade; repair of vehicles and motorcycles	2.52
Other activities	2.32
Manufacturing industry	1.74
Agriculture, forestry, hunting, fishing and fish farming	0.69
Education	0.53
Mining and quarrying	0.18
Least localized sectors	
Real estate activities	–0.10
Hotel activities and catering services	–0.09
Electricity, gas, steam, and air conditioning supply; water supply and water disposal; organization of waste collection and disposal; pollution-eliminating activities	–0.05

The analysis has revealed that industries depending on the resource base of the region are highly localized ones (agriculture, fishing and fish farming). Manufacturing industries, education and other FEA (financial, insurance, professional, scientific and technical activities, administrative and related additional services, public administration and military security; social security, activities in the field of culture, sports, leisure and entertainment) are localized due the availability of highly qualified personnel and developed infrastructure. These are localized mainly in Moscow, St. Petersburg, Kaluga Oblast, etc., with the largest investments in education, R&D and personnel training, and developed infrastructure. A high localization level of the trade industry is due to transport accessibility, and economic and geographical location.

As an example, the level of manufacturing industry localization is shown on **Figure 4**.

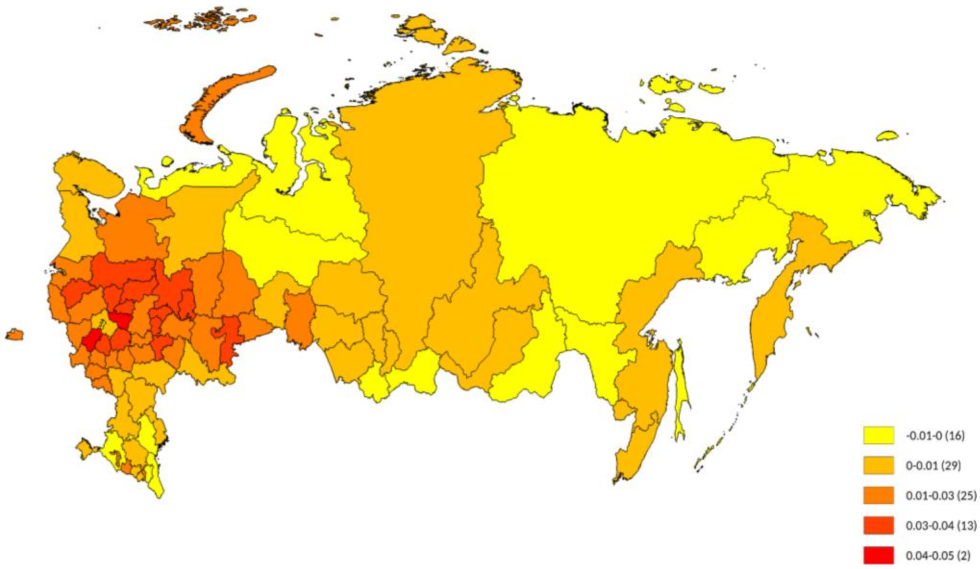

Figure 4. Localization level of manufacturing industry in Russian regions.

The least localized are the industries that are crucial for different regions and do not significantly depend on the resource base, infrastructure, or human capital. In particular, these are construction, hotel activities and catering services, and electricity, gas, steam, and water supply.

Table 5. Significant factors for assessing labor productivity in individual sectors of the economy by group of regions (clusters).

Economic sectors	Cluster 5	Cluster 6	Cluster 7
Agriculture, forestry, hunting, fishing and fish farming	-	LNZarp_2020	LNZarp_2020
Mining and quarrying	-	-	-
Manufacturing industry	LNZarp_2020	-	LNZarp_2020 Gruz_Rail_2020 Bezrab_2020
Electricity, gas, steam, and air conditioning supply; water supply and water disposal; organization of waste collection and disposal; pollution-eliminating activities	-	-	I_Trud_2020
Construction	-	-	LNZarp_2020
Wholesale and retail trade; repair of vehicles and motorcycles	LNZarp_2020	-	-
Transportation and storage	-	Collab_2019	I_Trud_2020
Hotel activities and catering services	-	LNZarp_2020	-
Information and communication activities	LNZarp_2020	-	LNZarp_2020
Real estate activities	-	LNZarp_2020	Bezrab_2020
Education	LNZarp_2020	-	Bezrab_2020
Human health and social care activities	LNZarp_2020	-	Gruz_Rail_2020 Bezrab_2020
Other activities	LNZarp_2020	LNZarp_2020	Bezrab_2020

The next step was an assessment of specification obtained for each cluster according to the parameters of various economic activity types in the region, and determination of significant factors. **Table 5** presents data on the factors that are significant in the considered set of regressors.

5. Discussion

Let us proceed to the description of the identified clusters (groups of regions) on the example of Cluster 7 in order to determine the industrial potential, socio-economic, innovative, and technological processes thereof for the subsequent development of the major directions for stimulating advancement and increasing agglomeration effects from FEA concentration in cluster regions.

Cluster 7 incorporates 39 regions, and many of them possessing low innovative and technological development.

An econometric model for Cluster 7 is as follows:

GRP_pc = –3258925.8 + 317972.6LNZarp + 45188.0Patent – 6228.9Bezrab + 2645.9Gruz_Rail + 2667.0I_Trud.

Cluster 7 is characterized by the lowest level of GRP per capita. The socio-economic potential of the incorporated regions is limited. There are no internal growth reserves; a strategic state support program for spatial development of these regions is required. A negative free parameter value can be interpreted as the lack of resources for potential growth, and the achievement of the maximum GRP value. There is a demand for economic and technological transformation to ensure a shift in the potential GRP curve. Thus, "Logarithm of the average monthly nominal accrued wages" (LNZarp) parameter turns out to be positive and significant.

On the one hand, these regions can be a springboard for the transfer of part of the production potential from other more developed regions. A high degree of diversification of the economy indicates the absence of clear proportions in the structure of the economy. The importance of the innovation factor suggests the prospects for creating innovative industries within these regions. The latter would introduce technologies supplied from other regions, for which it is advisable to transfer part of the innovation and technological factors to increase factor production efficiency. This should ensure building of the domestic Russian market and increasing inter-regional connectivity of production. Such approach should provide for a reduction in unemployment, an increase in wages and, in general, stimulation of GRP growth within the regions incorporated into this cluster. It is noteworthy that the labor productivity factor affects the growth of GRP.

A strong negative effect of unemployment, indicating the underestimation and underutilization of this factor, evidences the advisability of finding ways to increase productivity via the development of new industries that would create demand for domestic technologies and equipment. However, the regions of this cluster are national republics with a different type of economy. Accordingly, alternative mechanisms for regulating unemployment are urgent, and general recommendations for economic development are appropriate.

"Shipment of goods by public rail freight transport" (Gruz_Rail) parameter, being vital for this cluster, evidences a higher level of dependence on inter-regional industrial cooperation and transport accessibility as an element of stimulating economic growth. Therefore, an assessment of inter-regional economic spillovers might be of great importance for these regions.

Labor productivity in agriculture, forestry, hunting, and fishing depends on labor, wages and unemployment factors; in manufacturing industry—on labor, transport or infrastructure factors; in construction, information and communication activities – on labor factors; in education, real estate activities, and other FEA—on the unemployment factor; in human health and social care activities—on the transport factor (**Table 6**).

Table 6. Description and development vectors for the regions incorporated into Cluster 7.

Predisposition to FEA specialization	Characteristics	Determined efficient relationships, and demand for proportional and/or transformational changes within Model 1
Manufacturing industry, construction, trade, transportation and storage, education, and other FEA	Diversified economy. Low level of innovation development. Low level of GRP per capita. Low level of competition in existing markets.	There are numerous (15) regions with a single-valued efficiency, and some tending to be close to the optimum. Several regions lag behind a single-valued efficiency by 40–50%. There are regions with/without transformational changes for LNZarp, I_Trud, and Patent parameters, which indicates that optimization of relationships is possible in multiple directions. Transformational changes are required in Republic of Karelia, Saratov Oblast, and Altai Krai for Gruz_Rail parameter. Transformational changes are needed in Republic of Karelia, Republic of Dagestan, Republic of Ingushetia, Kabardino-Balkarian Republic, Karachay-Cherkess Republic, Republic of North Ossetia–Alania, Chechen Republic, Mari El Republic, Republic of Buryatia, and Jewish Autonomous Oblast for Bezrab parameter.

Thus, economic and technological transformation to stimulate GRP growth is essential. An important factor in stimulating economic growth could be infrastructure support and the development of transport and logistics infrastructure, since the regions of this cluster link the rest of the regions of our country. This would allow using labor potential thereof.

These regions could concentrate certain links in emerging new value added chains. It is necessary to develop construction, and communication and telecommunication industries to intensify inter-regional interactions in exchange for transport and logistics costs. This would ensure the expansion of the economy, and increase the level of its complexity to contribute to the subsequent growth of household incomes and GRP through the development of inter-sectoral and inter-regional cooperation.

It is necessary to advance related diversification, that is, to develop activities related to the current industry portfolio.

The state would play a vital role in creating an institutional environment and necessary conditions to stimulate the development of new industries in these regions, including high-tech ones, to reduce institutional barriers for entering new businesses in terms of regulatory support for production activities, and opportunities for using regional land resources and production platforms.

Here, it is advisable to use such instruments of regional economic policy as priority social and economic development areas (PSEDA), industrial clusters, technology parks, etc., and budget measures of regional policy concerning tax and tariff regulation.

Similarly, it is possible to analyze the results obtained and define directions for stimulating development and increasing agglomeration effects from FEA concentration for other clusters.

It is evident that regional provision of potentials (labor, capital, infrastructure, transport, institutional, innovative and technological, etc.) is of decisive importance in territorial-sectoral division of labor and localization of production. The proposed methodological approach opens the way to exploit the existing regional economic potential to the full, firstly, via establishing sectoral priorities of the region regarding the regulatory factors for the territorial capital to have a major effect on the increased potential GRP level; secondly, through benchmarking performance of the available development reserves within leading regions from homogeneous groups having similar characteristics and factor potentials; thirdly, via developing inter-regional integration prospects in terms of regional potential redistribution to ensure growth in potential gross domestic product.

6. Conclusion

A theoretical contribution of this research is that the proposed methodology allows for a holistic view of the regional development and the use of existing potentials through the coherent addressing of challenges facing processes of planning and justification of promising "smart" specializations and transformation vectors for regional economies. The clustering stage provides for considering the developed regional socio-economic potential and obtaining more homogeneous groups of regions. The benchmark-based DEA technique allows identifying the best experience of regions that have optimal structural proportions and development trajectory within each cluster. Besides it empowers substantiating the degree of proximity and similarity of development tracks and transformation within groups of regions. The econometric modeling stage enables validating the factors that dramatically affect the stimulation of GRP growth and transformational development of different regions.

Validation and testing of the conceptual model for spatial development (concentration, agglomeration, and clustering) is one of crucial outcomes of the conducted research. The underlying integrated approach to spatial development is based on consistent consideration of a number of aspects: firstly, the region's predisposition to the concentration of certain industries; secondly, the manifestation or operation of positive regional and sectoral agglomeration effects; finally, the feasibility of creating clusters based on these industries. Lack of coordination of these links could lead to such negative agglomeration effects as the accumulation of the population to the centers of regions and cities, negative migration, a decrease in the quality of life, the depopulation of peripheral areas, and, in general, low efficiency in the use of production factors.

This insight not only contributes to the academic discourse on complex territorial development, but also holds practical recommendations for government bodies of the constituent entities of the Russian Federation regarding the implementation of transformational economic policies and the design of effective regulatory mechanisms.

The obtained results provide arguments in favor of strengthening inter-regional connectivity and supporting inter-regional cooperation. Technical support related to infrastructure projects and institutional support aimed at strengthening cooperation and reducing barriers to spatial interaction contribute to addressing this issue.

The research results could be used for fine-tuning and building economic policies aimed at the development of certain regions and/or sectors. This would provide a shift from regional to inter-regional operation. Both aspects should be combined at the level of regional planning system, making appropriate mapping of the country's territory.

The achieved outcomes provide for assumptions about the effectiveness of policies aimed at developing industrial clusters, special economic zones or stimulating sectoral advancement. Theorized conclusions could be used as starting points or benchmarks in solving a challenging issue on the optimal sectoral distribution across regions.

In future, it is envisaged to construct logistic curves for assessing the level of technological maturity of sectors based on the calculation thereof for flagship companies (representatives of certain sectors) localized in the regions. The logistic curve tools would permit to evaluate and justify the very stage of technology (in terms of the volume of invested funds and the outcomes) at which a particular regional sector is located. The advantage of including such data in the analysis is the possibility to assess the degree for transformation demand relating to the technological limit achieved by the regional sector. An insight of the level achieved by each region allows for the combination of competencies and resources that various regional participants could bring to the industry cluster.

To consider regional connectivity, it is advisable to create a spatial weights matrix for assessing spatial effects of the regional transport infrastructure. Further, the resulting transport matrix should be overlayed on the initial clustering. To account for spatial regional connectivity according to individual parameters (including innovation and technology), one can apply various spatial autocorrelation tests, such as Wald test, Getis-Ord Gi* index, Geary criterion, and Moran's statistics being the most popular one.

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References

Aleschenko, O.A. (2020). "Smart Specialization" of Siberian Regions in Agricultural Production (Russian). ECO, 7, 111-129. https://doi.org/10.30680/ECO0131-7652-2020-7-111-129

Allen, T., & Arkolakis, C. (2018). Modern spatial economics: a primer. World Trade Evolution, 435–472. https://doi.org/10.4324/9781351061544-13

Artemova, O. V., Uzhegov, A.O. (2021). Differentiation of regions of the Russian Federation by socio-economic status (comparative analysis)—Interterritorial inequality: a problem or driver of development. Ekaterinburg: Institute of Economics of the Ural Branch of the Russian Academy of Sciences. pp. 79-86.

Barca, F., McCann, P., & Rodríguez-Pose, A. (2012). The case for regional development intervention: place-based versus place-neutral approaches*. Journal of Regional Science, 52(1), 134–152. Portico. https://doi.org/10.1111/j.1467-9787.2011.00756.x

Berchenko, N.G., Mishin, A.V. (2018). Practical aspects of definition of regional economic complexes perspective specialization. Economic Model Forecast, 12, 19-30.

Bukhvald E.M. (2018). "Self-development" of regions and the regulation priorities of the spatial structure of the economy of Russia (Russian). Federalism, (2), 32-45.

Bukhvald, E. M. (2023). Institutional Problems of Spatial Development Strategization. Federalism, 28(1), 80–98. https://doi.org/10.21686/2073-1051-2023-1-80-98

Davankov, A. Y., Degtyarev, P. Y., Dvinin, D. Y. (2020). Analysis of contradictions in the concentration of spatial landscapes in socio-ecological-economic systems. University Proc. Ural, 4, 7-14.

Degtyarev, P. Y. (2018). Enclosive disposition of spatial development of Russia. Bulletin Of Chelyabinsk State University, 7(417), 67–73. https://doi.org/10.24411/1994-2796-2018-10708

Demyanenko, A. (2020). Urban Agglomerations and Spatial Development Strategy: A Geographer's View. Regionalistica, 7(3), 43–52. https://doi.org/10.14530/reg.2020.3.43

Desmet, K., & Rossi-Hansberg, E. (2014). Spatial Development. American Economic Review, 104(4), 1211–1243. https://doi.org/10.1257/aer.104.4.1211

Druzhinin, P. V., Moroshkina, M. V., Sedova K. E. (2023). Development of agglomerations and economic growth of Russian regions (Russian). In: Proceedings of III Scientific and Practical Conference on Formation of Transport Systems and Socio-Economic Development of Urban Agglomerations. St. Petersburg: Institute on Regional Economy Problems.

Dubrovskaya, Y., Kudryavtseva, M., & Kozonogova, E. (2018). "Smart" Benchmarking as a Basis for Strategic Planning in Regional Development. Economic and Social Changes: Facts, Trends, Forecast, 3(57). https://doi.org/10.15838/esc.2018.3.57.7

Eferin, Y. Y., Kutsenko, E. S. (2021). Adjusting smart specialization concept for Russian regions (Russian), Public Adm, 3, 75-110.

Foray, D., Eichler, M., & Keller, M. (2020). Smart specialization strategies—insights gained from a unique European policy experiment on innovation and industrial policy design. Review of Evolutionary Political Economy, 2(1), 83–103. https://doi.org/10.1007/s43253-020-00026-z

Gamidullaeva L. A. (2023). Regional industrial cluster as a localized ecosystem: the role of self-organization and collaboration factors (Russian). π-Economy. https://doi.org/10.18721/JE.16105

Gamidullaeva, L. A. (2024). Smart specialization: Origin and State of the Art. MIR (Modernization. Innovation. Research), 15(1), 166–184. https://doi.org/10.18184/2079-4665.2024.15.1.166-184

Gamidullaeva, L., Korostyshevskaya, E., Myamlin, A., et al. (2022). Exploring Regional Industrial Growth: Does Specialization Explain It? Economies, 10(7), 172. https://doi.org/10.3390/economies10070172

Gamidullaeva, L., Strakhov, E., & Rzhevskaya, T. (2022). Systematization of clustering factors of economic entities in terms of the cluster life cycle. Models, Systems, Networks in Economics, Technology, Nature and Society, 4. https://doi.org/10.21685/2227-8486-2022-4-1

Gamidullaeva, L.A. (2023a) Smart Specialization: Origin and State of the Art (Russian). MIR (Modernization. Innovation. Research), 14(4).

Ivanov, O. B., Bukhvald, E. M. (1990). Spatial development strategy and the main directions of its updating. Available online: https://cyberleninka.ru/article/n/strategiya-prostranstvennogo-razvitiya-i-osnovnye-napravleniya-ee-aktualizatsii (accessed on 10 October 2023).

Kolmakov, V. V., Polyakova, A. G., Karpova, S. V., et al. (2019). Cluster Development Based on Competitive Specialization of Regions. Economy of Region, 15(1), 270–284. https://doi.org/10.17059/2019-1-21

Kolomak, E., & Sherubneva, A. (2023). Assessment of the Significance of Agglomeration Effects in the South of Siberia. Spatial Economics, 19(1), 52–69. https://doi.org/10.14530/se.2023.1.052-069

Korostyshevskaya, E. M., Gamidullaeva, L. A., Podkorytova, O. A. (2021). Impact of regional specialization on economic growth, in Fifth International Economic Symposium–2021. Available online: https://pure.spbu.ru/ws/portalfiles/portal/86621720/_.pdf. (accessed on 14 October 2023).

Kotov, A. V. (2022). Methodological approach to smart specialization for the Russian regions (Russian). EconSociol, 106(2), 22-45.

Kotov, A. V., Grishina, I. V., Polynev, A. O. (2019). Smart Regional Specialization—a Solution for Russia: A Scientific Essay, Moscow (Russian). RFTA, 2019.

Kranjac, M., Sikimic, U., Salom, J., et al. (2018). Visualization of smart specialisation process using QGIS tools. 2018 41st International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO). https://doi.org/10.23919/mipro.2018.8400260

Kroll, H. (2015). Efforts to Implement Smart Specialization in Practice—Leading Unlike Horses to the Water. European Planning Studies, 23(10), 2079–2098. https://doi.org/10.1080/09654313.2014.1003036

Kuleshov, V. V., Seliverstov, V. E. (2018). Siberia's role in the spatial development of Russia and its positioning in the Russian Federation spatial development strategy. Region: ekonomika i sotsiologiya, 4(96), 3–24. https://doi.org/10.15372/reg20180212

Kutsenko, E., & Eferin, Y. (2019). “Whirlpools” and “Safe Harbors” in the Dynamics of Industrial Specialization in Russian Regions. Foresight and STI Governance, 13(3), 24–40. https://doi.org/10.17323/2500-2597.2019.3.24.40

Kuznetsov, S., Shamakhov, V., & Mezhevich, N. (2019). Strategy of Spatial Development of the Russian Federation and Prospect of Seaside Agglomerations Development. Administrative Consulting, 10–18. https://doi.org/10.22394/1726-1139-2019-6-10-18

Kuznetsova, O. V. (2019). Problems of Elaboration of Spatial Development Strategy of the Russian Federation. Spatial Economics, 15(4), 107–125. https://doi.org/10.14530/se.2019.4.107-125

Kuznetsova, O. V. (2019). Settlement transformation and the problems of its adequate consideration in the spatial development strategy. Population and Economics, 3(1), 53–62. https://doi.org/10.3897/popecon.3.e34777

Kvint, V. L. (2019). Territory of semi-trailers. Does Russia need a spatial development strategy (Russian). Available online: https://www.kommersant.ru/doc/3908584 (accessed on 14 October 2023).

Lebedev, K. V., Vasilyeva, L. V., & Sumenova, E. S. (2022). Economy regional features and specialist training structure. Vestnik Universiteta, 1, 99–108. https://doi.org/10.26425/1816-4277-2022-1-99-108

Lukin, E. (2019). Sectoral and Territorial Specifics of Value-Added Chains in Russia: the Input-Output Approach. Economic and Social Changes: Facts, Trends, Forecast, 6(66). https://doi.org/10.15838/esc.2019.6.66.7

Lukin, E. V. (2023). Economy of North-West Russia: in search of promising specialization. ECO, 53(8), 8–34. https://doi.org/10.30680/eco0131-7652-2023-8-8-34

Lukin, E., Anosova, T., Mel’nikov, A., et al. (2020). Experience in Agent-Based Modeling of Interregional Value Chains. Economic and Social Changes: Facts, Trends, Forecast, 6(72). https://doi.org/10.15838/esc.2020.6.72.6

MAEF. (2023). V Moscow Academic Economic Forum Took Place in the Great Hall of the Russian Academy of Sciences. Available online: https://maef.veorus.ru/news/08-06-2023-2 (accessed on 6 March 2024).

Makar, S. V., Yarasheva, A. V. (2022). Cluster approach to the organization of national space: The possibility of industrial and regional symbiosis (Russian). In: Clustering of Digital Economy: Theory and Practice. St. Petersburg: Polytech-Press. pp. 211-267.

Makhanov K. (2019). The New Spatial Development Strategy of Russia (approved by Order of the Government of the Russian Federation no. 207-r). Eurasian research institute.

Martin, P. (2015). The Geography of Inequalities in Europe. Swedish Economic Policy Review, 12, 83-108.

Mikheeva, N. N. (2018). Strategy of spatial development: New stage or repetition of old mistakes (Russian)? ECO, 48(5), 158-178. http://doi.org/10.30680/ECO0131-7652-2018-5

Minakir, P. (2018). Spatial Development Strategy: A View from the Concepts of Spatial Organization in the Economy. Spatial Economics, 4, 8–20. https://doi.org/10.14530/se.2018.4.008-020

Minakir, P. A. (2015). Spatial interdisciplinary synthesis: Experience of policy studies. Regional Research of Russia, 5(4), 299–309. https://doi.org/10.1134/s2079970515040115

Moiseev, A. K., Bondarenko, P. A. (2020). Application of the economic complexity index in macro-financial models (Russian). Probl. Forecast, 3, 101-112.

Orlova, L. N., Cse, Ya. M. (2024). The concept of “smart specialization” for innovative development of Russian regions. Public Administration. E-Journal, 102, 37–53. https://doi.org/10.55959/msu2070-1381-102-2024-37-53

Paap, J. (2020). Mapping the Technological Landscape to Accelerate Innovation. Foresight and STI Governance, 14(3), 41-54. https://doi.org/10.17323/2500-2597.2020.3.41.54

Rastvortseva, S., & Amanalieva, A. (2021). The concept of technological proximity in the development of European Union national innovative systems. Bulletin of Geography. Socio-Economic Series, 51(51), 35–45. https://doi.org/10.2478/bog-2021-0003

Rumyantsev, N., Leonidova, E., & Gubanova, E. (2022). Defining Sectoral Priorities of the Region’s Structural Transformation by Searching for Promising Economic Specializations. Economic and Social Changes: Facts, Trends, Forecast, 6(84). https://doi.org/10.15838/esc.2022.6.84.5

Yilmaz, E., & Sensoy, F. (2023). Reassessment of the Todaro Paradox: An Extended Panel Data Analysis on Developing Countries. Economic and Social Changes: Facts, Trends, Forecast, 2(86). https://doi.org/10.15838/esc.2023.2.86.11

Zyuzin, A. V., & Demidova, O. A. (2022). Impact of industry clusters on the performance of Russian private companies: Inter-industry analysis. Voprosy Ekonomiki, 11, 90–116. https://doi.org/10.32609/0042-8736-2022-11-90-116

Zyuzin, A., Demidova, O., & Dolgopyatova, T. (2020). Localization and Diversification of Russian Economy: Regions’ and Industries’ Peculiarities. Spatial Economics, 16(2), 39–69. https://doi.org/10.14530/se.2020.2.039-069