Competitiveness of Russian regions in the context of the digital divide

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Abstract. The socio-economic inequality of the Russian Federation entities generates digital inequality, and affects the competitiveness of the agglomerations. The purpose of the study is to assess the impact of digital inequality on the Russian regions competitiveness level. The direct connection between the levels of ICT development and regional competitiveness is the hypothesis of the study. Therefore, regions with the similar characteristics of ICT development will have the same competitiveness level. We use the cluster analysis to test the hypothesis. As a result of the research, we confirm the hypothesis, according to the data characterizing the Russian economy in a four-year time interval.

Keywords: Socio-economic inequality of regions, regional competitiveness, entities of the Russian Federation, cluster analysis, ICT development, digital divide.

JEL codes: B41, O30, R11

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Introduction

ICT is a basic element of the innovation environment infrastructure of an agglomeration. It has a direct impact on regional competitiveness. Directly, by accelerating information exchange, reducing transaction costs, creating new services and products, and indirectly, by improving the quality of life of the population.

The connection between regional competitiveness and innovation in the economic literature has long been identified: starting from the works of the "founder" of the national competitiveness concept M. Porter and ending with the research of modern authors (Shkiotov, 2022). Indeed, Polyakova, Kolmakov & Yamova (2019) consider the regional competitiveness as a function of innovation activity; Naibaho (2021) shows how regional innovation policy stimulates the competitiveness of agglomeration; Zinovyeva et al. (2016) verifies the hypothesis of the innovative development impact on regional competitiveness; studies by Petronela & Cojanu (2013); Sabatino & Talamo (2017); Csete & Barna (2021) concern with the same relationships, but on the example of European regions.

The issue of these research in term of the Russian regions competitiveness is often associated with a number of complex tasks: starting with the choice of research methodology and ending with the lack of a regional competitiveness significant statistical base. Moreover, the competitiveness of Russian regions is greatly influenced by their socio-economic inequality (Shkiotov, 2022).

In this study we will analyse the relationship between the development of ICT by the cluster analysis at the level of the Russian Federation entities and the level of their competitiveness.

The research issue allows us to identify the relationship between the development of ICT and competitiveness, along with the factor of regional socio-economic inequality (in this context, digital).

Methods

The direct connection between the level of ICT development and the level of regional competitiveness is the hypothesis of the study. Therefore, regions with the similar characteristics of ICT development will have the same competitiveness level.

Research methodology

1. The study period is 4 years (short-term).

2. Indicators used:

Indicators characterizing the development of ICT in Russia:

- Number of fixed telephony subscribers per 100 residents in the Russian Federation, 2000-20 (FTS);
- Number of mobile phone subscribers per 100 residents in the Russian Federation, 2000-20 (MTS);
- Number of fixed broadband subscribers per 100 residents in the Russian Federation, 2011-20 (FBS);
- Number of Internet users, % of the population in the Russian Federation, 2014-20 (IU).

Indicators characterizing the level of competitiveness of the Russian Federation entities:

- Rating of Russian regions competitiveness AV RCI, 2018-21.

All the data used in the paper are taken from: Rosstat, Resource Center for Strategic Planning (https://stratplan.ru /). The dynamics of the studied indicators is shown in Figures 1 and 2.

3. Sample: 85 entities of the Russian Federation; 4-year time interval (2018-21).

4. Research methods: cluster analysis. In general, cluster analysis is designed to combine some objects into classes (clusters) in a way which maximises the similarity of objects in one class and maximises the difference between the objects of different classes. The quantitative similarity indicator is calculated in a proper way on the basis of data characterizing the entities. In this case, the aim of the cluster analysis is to divide the RF entities into classes, each corresponding to a particular group (with the same characteristic of ICT development). Note that all clustering algorithms need assessments of distances between clusters or objects, for which the scale of measurement is required. Since different measurements use completely different types of scales, the data should be standardised so that each variable has a mean of 0 and a standard deviation of 1.

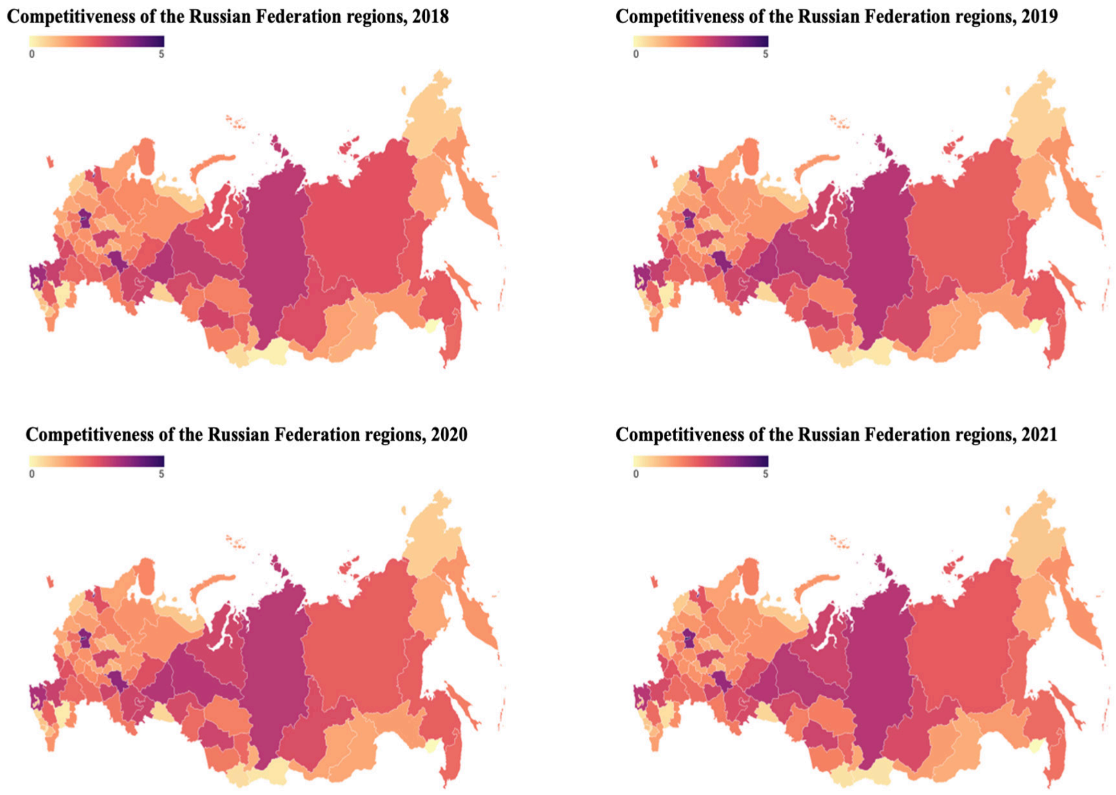

Figure 1. Competitiveness of the Russian Federation regions, 2018-21

Source: Russian Regions Competitiveness Index AV RCI , 2018-21

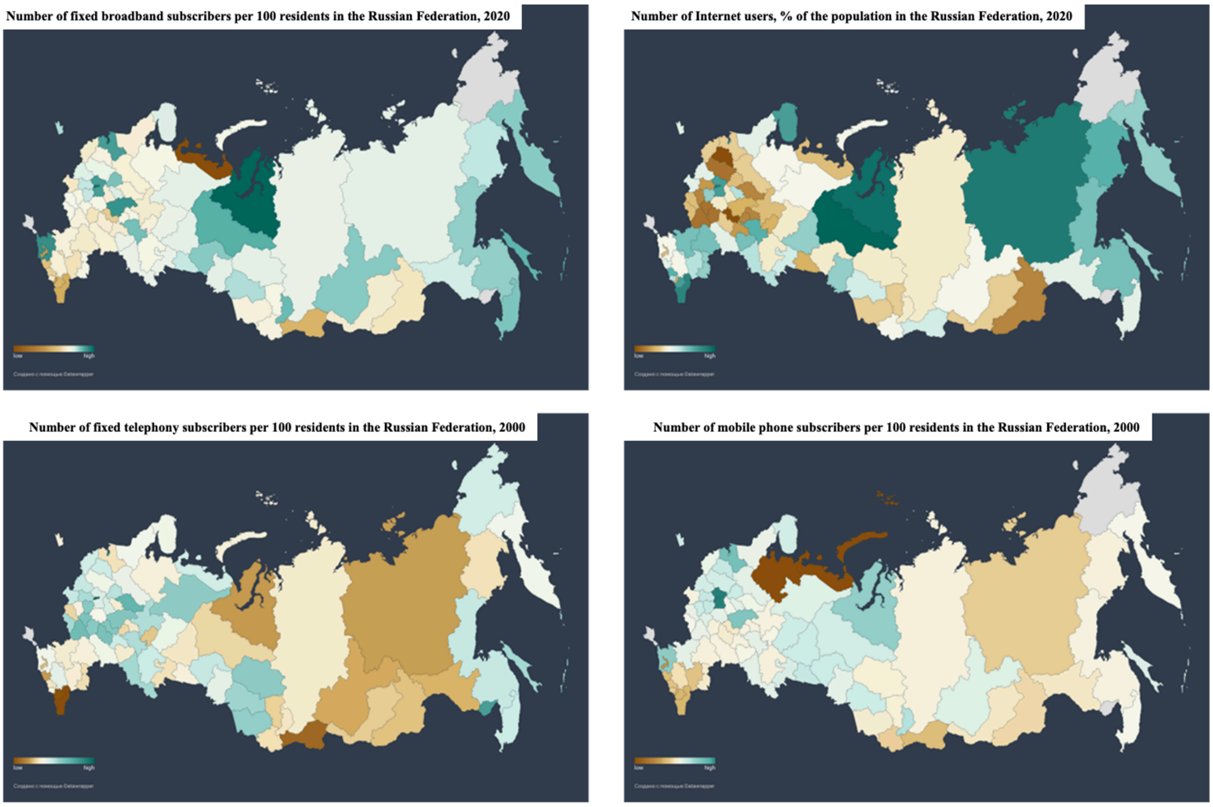

Figure 2. The development of ICT in the Russian Federation regions, 2020
Source : Rosstat, 2016-20

Research progress

At the first stage of the study, we will find out whether the regions form "natural" clusters that can be comprehended.

The full link method defines the distance between clusters as the largest distance between any two objects in different clusters. The proximity measure defined by the Euclidean distance is a geometric distance in n-dimensional space and is calculated as follows:

$$d(x, y,) = \sqrt{\sum (x_i - y_i)^2} \tag{1}$$

The most important result obtained as a result of tree clustering is a hierarchical tree (see Fig. 3).

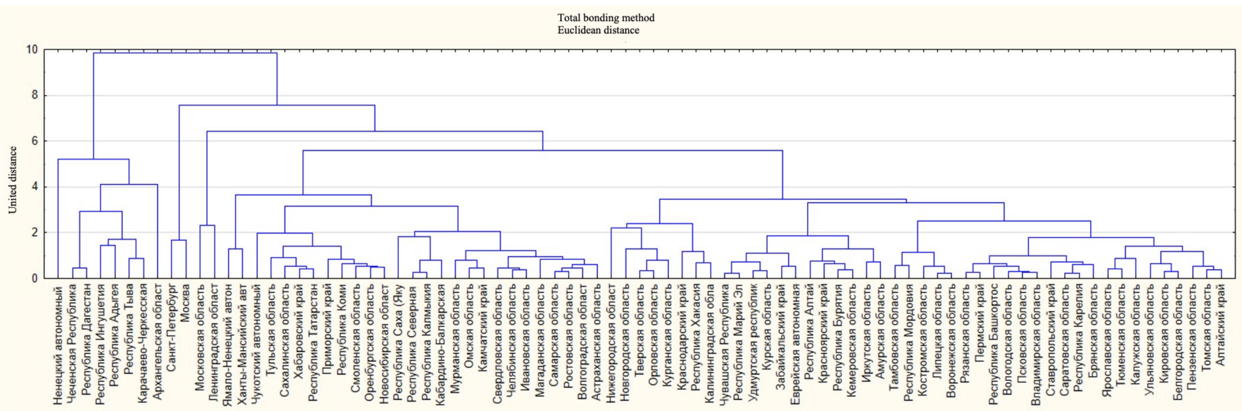

Figure 3. Vertical dendrogramme by constituent entities of the Russian Federation
Source: composed by authors

The analysis of the diagram starts from the top (for a vertical dendrogram) with each region in its own cluster.

When we down from the top the adjacent regions form the clusters. Each node in the diagram above represents a union of two or more clusters, the position of the nodes on the vertical axis determining the distance at which the respective clusters have been joined.

Based on the visual representation of the results, we can assume the formation of five natural regional clusters. We can test this assumption by dividing the initial data by the K-means method into 5 clusters, and checking the significance of the difference between the groups obtained.

The K-means method is as follows: calculations begin with k randomly selected observations (in our case k=4), which become the centers of groups. Then the object composition of clusters changes in order to minimize variability within clusters and maximize variability between clusters. Each subsequent observation (K+1) belongs to the group which similarity measure with the center of gravity is minimal. After changing the cluster composition, a new center of gravity is calculated, most often as a vector of averages for each parameter. The algorithm works until the composition of the clusters stops changing. When the classification results are obtained, we can calculate the average value of the indicators for each cluster to assess their differences.

To determine the significance of the difference between the obtained clusters In the analysis of variance, we use a p-value of 5% (a value of $p < 0.05$ indicates a significant difference).

Table 1 – Results of the variance analysis

	Between - SS	ss	Inside - SS	ss	F	significant. -p
FTS 2020	39,91118	4	42,08882	78	18,49109	0,000000
MCS 2020	54,75084	4	27,24916	78	39,18070	0,000000
FBS 2020	60,78172	4	21,21828	78	55,85956	0,000000
IU 2020	48,49548	4	33,50452	78	28,22490	0,000000

Source: ccomposed by authors

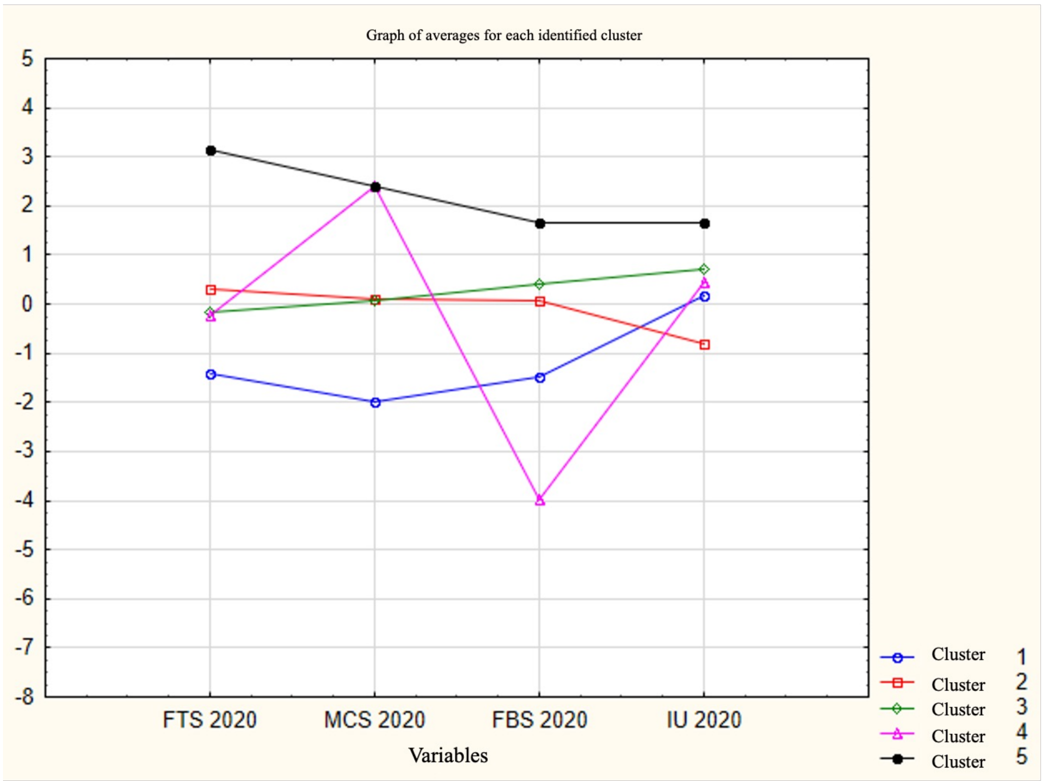

Figure 4. Graph of averages for each identified cluster

Source: composed by authors

Results

Therefore, each of the five analyzed clusters contains the objects with similar characteristics of ICT development.

Table 2 – Cluster elements number 1 (ICT development 2016-2020-normal.sta) and distances to the cluster center

The Russian Federation entity	united .
Arhangelsk region	1,368331
Karachay-Cherkess Republic	0,499598
Nenets Autonomous Okrug	1,835369
Republic of Adygea	0,497613
The Republic of Dagestan	1,018835
The Republic of Ingushetia	0,764094
Tyva Republic	0,539968
Chechen Republic	0,855668

Source: composed by authors

Table 3 – Cluster elements number 2 (ICT development 2016-2020-normal.sta) and distances to the cluster center

The Russian Federation entity	united .
Altai region	0,406289
Belgorod region	0,246388
Bryansk region	0,517195
Vladimir region	0,281692
Vologda Region	0,231457
Voronezh region	0,694870
Jewish Autonomous Region	0,518757
Transbaikal region	0,775763
Kaluga region	0,439424
Kemerovo region	0,578819
Kirov region	0,249924
Kostroma region	0,766736
Krasnoyarsk region	0,482026
Kurgan region	0,438232
Kursk region	0,520861
Lipetsk region	0,613329
Nizhny Novgorod Region	1,056106
Novgorod region	0,624760
Oryol Region	0,404696
Penza region	0,578855
Perm region	0,344203
Pskov region	0,210207
Republic of Bashkortostan	0,288610
The Republic of Buryatia	0,653361
Komi Republic	0,519518
Mari El Republic	0,471436

The Russian Federation entity	united .
The Republic of Mordovia	0,821095
Ryazan Oblast	0,327270
Stavropol region	0,500585
Tambov Region	0,575846
Tver region	0,404463
Tomsk region	0,479782
Tyumen region	0,469883
Udmurt republic	0,590485
Ulyanovsk region	0,200521
Chuvash Republic	0,566949
Yaroslavl region	0,443104

Source: composed by authors

Table 4 – Cluster elements number 3 (ICT development 2016-2020-normal.sta) and distances to the cluster centerr

The Russian Federation entity	united .
Amur region	0,583679
Astrakhan region	0,360636
Volgograd region	0,328749
Ivanovo region	0,152850
Irkutsk region	0,647906
Kabardino-Balkarian Republic	0,799467
Kaliningrad region	0,372107
Kamchatka Krai	0,166887
Krasnodar region	0,877195
Magadan Region	0,346635
Murmansk region	0,359722
Novosibirsk region	0,564676
Omsk region	0,163260
Orenburg region	0,493759
Primorsky Krai	0,439428
Altai Republic	0,657792
Republic of Kalmykia	0,666258
Republic of Karelia	0,390542
The Republic of Sakha (Yakutia)	0,925665
Republic of North Ossetia - Alania	0,554175
Republic of Tatarstan	0,530108
The Republic of Khakassia	0,703398
Rostov region	0,289221
Samara Region	0,196227
Saratov region	0,391625
Sakhalin region	0,545727

The Russian Federation entity	united .
Sverdlovsk region	0,276255
Smolensk region	0,464011
Tula region	0,680609
Khabarovsk region	0,380432
Khanty-Mansi Autonomous Okrug - Yugra	0,944547
Chelyabinsk region	0,333044
Chukotka Autonomous Okrug	0,775715
Yamalo-Nenets Autonomous Okrug	1,285826

Source: composed by authors

Table 5 – Cluster elements number 4 (ICT development 2016-2020-normal.sta) and distances to the cluster center

The Russian Federation entity	united .
Leningrad region	0.578400
Moscow region	0.578400

Source: composed by authors

Table 6 – Cluster elements number 5 (ICT development 2016-2020-normal.sta) and distances to the cluster center

The Russian Federation entity	united .
Moscow	0.417757
Saint Petersburg	0.417757

Source: composed by authors

Now it is possible to calculate basic descriptive statistics for each cluster. We make a graph of the average and confidence intervals for variables in each cluster (see Figure 5)

Below is a table of descriptive statistics for each of the indicators (see Table 7).

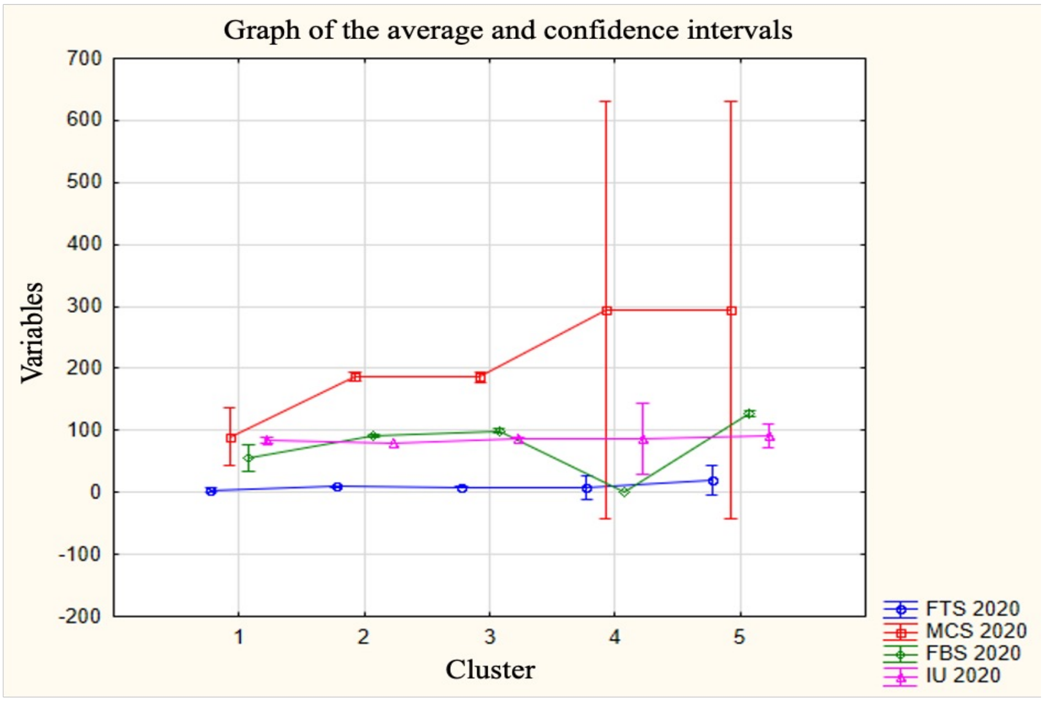

Figure 5. Graph of the average and confidence intervals for variables in each cluster
Source: composed by authors

Below is a table of descriptive statistics for each of the indicators (see Table 7).

Table 7 – Final table of averages

Cluster	FTS 2020	MCS 2020	FBS 2020	IU 2020
1	3,7675	89,1425	56,225	84,125
2	9,81608	186,2835	91,5676	79,40541
3	8,18221	185,9712	98,9441	86,88235
4	7,98	294,535	0	85,5
5	19,87	294,535	127,4	91,5

Source: composed by authors

At the second stage of our research, we will analyze the competitiveness of the regions according to the clusters identified above. We can assess the average value of the regions competitiveness in each selected cluster and analyze the level of regional competitiveness for each isolated cluster.

We will use the t-criterion for independent samples. The grouping variable "klasters" splits the data into groups. Cluster samples will be compared relative to the average of their scores on each scale.

Table 8 – Results of the assessment of the regional competitiveness average level for identified clusters

	Average - 1	Average - 2	t-value	Degree of freedom	p	N obs. - 1	N obs. - 2	Standard deviation - 1	Standard deviation - 2	F-relative dispersion	p - variance
t -criterion; Grouped .: klasters (ICT Development 2016-2020.sta) Group 1:1 Group 2:2											
Competi-tiveness 2020	0.841250	1.714324	-3.44113	43	0.0013	8	37	0.490115	0.677535	1.911029	0.378057
t -criterion; Grouped .: klasters (ICT Development 2016-2020.sta) Group 1:1 Group 2:3											
Competi-tiveness 2020	0.841250	1.970588	-3.54639	40	0.0010	8	34	0.490115	0.863190	3.101823	0.123226
t -criterion; Grouped .: klasters (ICT Development 2016-2020.sta) Group 1:1 Group 2:4											
Competi-tiveness 2020	0.841250	3.160000	-5.29969	8	0.0007	8	2	0.490115	0.876812	3.200500	0.233499
t -criterion; Grouped .: klasters (ICT Development 2016-2020.sta) Group 1:1 Group 2:5											
Competi-tiveness 2020	0.841250	4.515000	-8.95983	8	0.0000	8	2	0.490115	0.685894	1.958474	0.408795
t -criterion; Grouped .: klasters (ICT Development 2016-2020.sta) Group 1:2 Group 2:3											
Competi-tiveness 2020	1.714324	1.970588	-1.39742	69	0.1668	37	34	0.677535	0.863190	1.623117	0.157386
t -criterion; Grouped .: klasters (ICT Development 2016-2020.sta) Group 1:2 Group 2:4											
Competi-tiveness 2020	1.714324	3.160000	-2.91272	37	0.0060	37	2	0.677535	0.876812	1.674752	0.407728
t -criterion; Grouped .: klasters (ICT Development 2016-2020.sta) Group 1:2 Group 2:5											
Competi-tiveness 2020	1.714324	4.515000	-5.69206	37	0.0000	37	2	0.677535	0.685894	1.024827	0.636265
t -criterion; Grouped .: klasters (ICT Development 2016-2020.sta) Group 1:3 Group 2:4											
Competi-tiveness 2020	1.970588	3.160000	-1.89289	34	0.0669	34	2	0.863190	0.876812	1.031813	0.634247
t -criterion; Grouped .: klasters (ICT Development 2016-2020.sta) Group 1:3 Group 2:5											
Competi-tiveness 2020	1.970588	4.515000	-4.07335	34	0.0003	34	2	0.863190	0.685894	1.583796	1.000000

Source: compiled by the authors

The fastest way to analyze Table 9 is to view the fifth column (containing p-levels) and determine which of the p-values are less than the established significance level of 0.05. The averages for the two groups are different for the most dependent variables.

The graph for these resulting tables (7-8) is the box plot (see Figure 6).

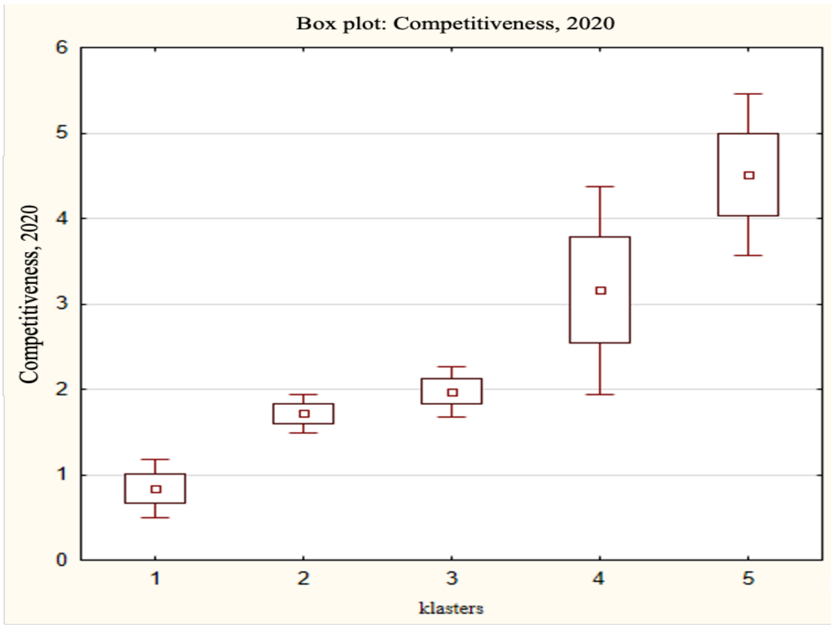

Figure 6. Span Diagram

Source: composed by authors

The difference is more significant the averages in Figure 6 and cannot be explained by the the variability of the initial data. Indeed, there is unexpected difference on the constructed graph. The variance for cluster groups 4 and 5 is greater than for 1-3 (rectangles representing standard deviations equal to the square root of the variation). If the variances in the two groups differ significantly, the one of the requirements for the use of the t-test is violated. This difference should be considered in further studies.

Conclusions

We confirmed the hypothesis by the results of our research. Regions with similar characteristics of ICT development are in the same group in terms of regional competitiveness. Hence, the development of ICT (digital inequality in the context of Russian regions) has a direct impact on the competitiveness of the agglomeration.

The obtained research results can be explained by the limitations of the model used (insufficient sampling for cluster analysis; changes in the methodology of data collection, and assessment of complex indicators).

Thus, the result could activate a new applied research on the competitiveness of Russian regions in the context of digital inequality.

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