

## ***E-Government clusters in the EU based on the Gaussian Mixture Models***

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**Abstract:** *The use of advanced ICT technologies and the support of new ways of thinking, acting and working in public administration, together with the increased provision of information and interactive services accessible through various channels, is the foundation of eGovernment. In recent years, there has been visible progress in all EU countries in terms of the general framework for e-government strategy, which is based on best practices and methodologies. The aim of our research is to discover the way in which the EU states are situated from the point of view of the digitalization of the administration. For this I used Gaussian models. The main research parameters were: accessibility; transparency, investments in information and communication technologies and investments in infrastructure related to public administrations in EU countries. The results show significant differences between state administrations. We applied Gaussian Mixture Model clustering in order to make an analysis of the national E-government situation in the European Union for 2018. The GMM algorithm estimated six clusters. We find that the first cluster, with Nordic countries, Netherlands and Austria, has the highest values of telecommunication infrastructure, citizens' access to e-government services and Transparency International's Corruption Perception Index. At the opposite pole, in cluster 2, Romania and Bulgaria have the lowest values of these three indicators, while their public investment levels are not significantly under EU averages. Our research provides not only an overview of the digitization of administrations, but also what are the main lags that state administrations have to recover in order to reach a digital system integrated into the EU's administrative space.*

**Keywords:** Clustering, Digitalization, E-Government, European Union, Gaussian Mixture Models

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## **Introduction**

We live in a world in which the citizen becomes more and more aware of his rights and role in society, coming in addition to the obligations that the state expects him to fulfill. This situation is naturally generated by the changes that the public administration is going through in all the member states of the European Union, including Romania (Zeibote et al., 2019; Barmuta et al. 2020; Lincényi and Čársky 2020). The implementation and widespread use of e-government services for citizens and the business environment, complemented by the mobility offered by modern electronic communications equipment, take the use of technologies and digitization to another level in the Romanian communities and worldwide. In this context, the following authors formulated other factors that the quality of the business environment is determined by the state policy support (Khan et al., 2019; Kvanina et al., 2019), strategic human resources management (Dvorsky et al., 2020; Sabie et al., 2020; Lemke, 2019), or level of implementation of corporate social responsibility (Metzker & Streimikis, 2020; Meilhan, 2019). E-Government is important for OECD and EU member states and EU neighbors (Balzer et al., 2020; Kovacova et al., 2019; Nica et al.2019; Sidorenko et al., 2019). The usefulness of this activity is necessary for public institutions (Vlăcseková, 2019; Revyakin, 2019), private agencies, where different alternatives must be chosen for the implementation of projects or e-Government activity. Measuring the quality of a service provided by e-Government is of special importance, as most public administrations have as a major objective the improvement of the quality of services provided to citizens (Eskridge, 2019). Quality standards vary from service to service or from institution to institution. They must be developed in the context of service rules and standards and building a European system oriented towards society (Shpak et al., 2019; Gajdoš & Hudec, 2020; Kotnik et al. 2020). Both quantitative and qualitative indicators are used to evaluate e-Government services. They aim to capture as well as possible the diversity and complexity of the services used (Peters M.A.& Besley, 2019). Among those E-services, especially customs system is worth a special attention. That's because it largely determines the ease of conducting international trade, the security of international supply chains and first of all, economic development of the countries (Shpak et al., 2020).

### **1. Digitalization of public administration and e-governance in the literature**

"eEurope 2005" was an important part of the Lisbon strategy, which focused on social cohesion and the transformation of the European economy into the most dynamic and competitive economy (Popescu G. H. & Ciurlău, 2019). That is why the "eEurope 2005" action plan contained measures to include information technologies in all areas (creation of multiple platforms for various types of services). The action plan had two large groups of mutually supportive sub-actions:

stimulating services and implicitly developing digital content on the one hand, and developing infrastructure (broadband networks and network security) on the other.

The action plan also aimed to:

- modern online public services (eGovernment);
- eLearning services;
- eHealth services;
- a dynamic eBusiness environment;
- wide availability for access to communication networks (cheap and fast internet);
- secure information infrastructure (information and network security).

This action plan had to be supported by financial instruments of the states implementing these actions. The “eEurope 2005” plan recommends 4 tools for its implementation:

- policy measures for the review and adaptation (harmonization) of legislation at national and European level;
- strengthening interoperability;
- improving access to communication networks;
- political will (national strategy in the field) for the implementation of the information society in European countries.

“eEurope 2005” has identified those areas in which, through an appropriate public policy, added value can be added to activities and actions in the socio-economic life of a country. The plan focused on a limited set of actions with well-defined key targets:

1. connecting public administration services and schools to broadband networks;
2. creating interactive public services accessible to all and on multiple platforms;
3. online health services;
4. review and harmonization of eBusiness legislation;
5. creating a cyber security task force (“Cyber Security Task Force”).

Unitary actions at European level fall into three strategic elements described in the Lisbon document:

- transforming the European Union into a viable alternative;
- developing the knowledge and innovation society through the development of ICT;
- creating highly qualified and well-paid jobs;

The efficiency of the implementation of the action plans can be grouped as follows:

- from a political point of view, conditions were created for the accession to the European Union of other countries that were not yet members of the EU (the case of Romania and Bulgaria);
- from a legislative point of view, a unitary framework has been created at European level for the Information Society;

- easier integration of citizens into the European space, regardless of ethnicity and belonging to a certain nationality.
- i2010 focused on the development of the digital economy. In line with this strategy, the European Parliament and the Council of Europe have established a multiannual program, a timetable for digital content in Europe that is accessible and usable. The central objective for eContent is to disseminate information in the area of public interest (Mura & Machyniak, 2014). eContent and the i2010 strategy aim to eliminate the so-called "digital divide" in fact reduce discrimination between those who know and can use the computer and those who do not know and/or can not use the computer because they have no conditions, a fact generated by economic and social effects on the environment in which they live (Stare & Klun, 2018). Digitalization can eradicate "digital divide" via relevant accessibility to bank services (Bhukuth & Terrany, 2019), capabilities of decent work due to ICT technologies (Kolot et al., 2020) and overall digital transformation of business activity (Bilan et al., 2019).

At European level, the performance of each country is measured by two indicators: Access and Digitization (Jeretina, 2018). The Degree of Access describes the extent to which the online environment is used at the level of administrative services, while digitization takes into account the level of digitization of public administration counters.

Romania has an above average level (63%; EU average 57%) of using the online channel in administrative services (Access) and a low level (40%; EU average 68%) of administrative digitization (Digitization).

Our research included all EU Member States where we analyzed in 2018 the impact of the EU strategy for digitization and e-government using the Gaussian Mixture Model.

## **2. Research methodology and data analysis**

### **2.1 Research database**

The analysis is conducted on 28 European Union countries as of 2018: Austria (AUT), Belgium (BEL), Bulgaria (BUL), Croatia (HRV), Czech Republic (CZE), Denmark (DNK), Estonia (EST), Finland (FIN), France (FRA), Germany (GER), Greece (GRC), Hungary (HUN), Ireland (IRE), Italy (ITA), Latvia (LAT), Lithuania (LIT), Luxembourg (LUX), Malta (MLT), Netherlands (NLD), Poland (POL), Portugal (PRT), Romania (ROU), Slovakia (SVK), Slovenia (SVN), Spain (ESP), Sweden (SWE), and - still the EU member at the time - United Kingdom (GBR).

Five variables have been collected as features of the national E-Government situation in each country. These variables include (i) Telecom Infrastructure, (ii) Access to E-Government services, (iii) Corruption Perception

Index, (iv) public investments to R&D in ICT sector, and (v) public investments to R&D in ICT as a share of total R&D investments. The variables and data sources are shown in Table 1.

**Table 1. Features of E-Governments**

<b>Name</b>	<b>Description</b>	<b>Data Source</b>
V1 – Infra	Telecom Infrastructure Index	<a href="https://publicadministration.un.org/egovkb/en-us/Data-Center-UN">https://publicadministration.un.org/egovkb/en-us/Data-Center-UN</a>
V2 – E-Gov't Access	Internet access to services of public administration	<a href="https://ec.europa.eu/eurostat/databrowser/view/TIN00012/default/table">https://ec.europa.eu/eurostat/databrowser/view/TIN00012/default/table</a> (Eurostat)
V3 – CPI	Corruption Perception Index (Transparency International)	<a href="https://www.transparency.org/en/cpi/2018/results">https://www.transparency.org/en/cpi/2018/results</a> (EC)
V4 – ICT_GBARD	Public R&D investment in ICT	<a href="https://visualise.jrc.ec.europa.eu/t/PREDICT/views/PREDICT_2020_15942949318610/Story1?isGuestRedirectFromVizportal=y&amp;embed=y">https://visualise.jrc.ec.europa.eu/t/PREDICT/views/PREDICT_2020_15942949318610/Story1?isGuestRedirectFromVizportal=y&amp;embed=y</a> (EC)
V5 – ICT_GBARD / GBARD (%) – V5	%-share of public R&D investment in ICT of total R&D investments	

*(Source: Authors)*

Gaussian Mixture Model belongs to the class of model-based clustering or distribution models. GMM is based on a formal data model and uses an expected-maximization (EM) algorithm to estimate the model components and the appropriate number of clusters. The dataset is associated with a distribution that is a mixture of two or more clusters. Each cluster is characterized by a Gaussian distribution, which is a very frequent distribution.

The basic approach to cluster data is K-means algorithm. One drawback of the K-means algorithm is that the clusters obtained are round –shaped, since the distance is measured from the cluster center. Another drawback is that each object belongs only to one cluster, but in reality, some clusters overlap, and an object belongs to a cluster with a certain probability. For avoiding these drawbacks, the Gaussian mixture model was introduced, having a probabilistic approach. In GMM, each cluster is characterized by its mean, covariance matrix and weight (cluster size). One fits a set of k Gaussians to the data, then one estimates the parameters of the Gaussian distribution such as mean, covariance matrix and weight by means of EM algorithm, such as they have a maximum likelihood fit to the model. In the end one computes the probability of each object to belong to a cluster.

The EM algorithm starts with a random initialization and has two iterative steps:

- E-Step: The expected probabilities of objects to clusters are determined, based on the current model parameters;

- M-Step: The optimal model parameters of each mixture are determined using the probabilities as weights.

**2.2 Data analysis**

In real world it is assumed that a data distribution is unimodal. For theoretical reasons it is assumed that the most frequently distribution that models unimodal real-world data is the Gaussian distribution.

A Gaussian mixture model is a probabilistic model, in which the data are extracted from several Gaussian distributions whose parameters are not known. We will apply GMM clustering.

We will determine the optimal model which gives the number of clusters according to the Bayesian Information Criterion for expectation-maximization algorithm. The best three selected models provided by R environment based on the Bayesian Information Criterion (BIC) are shown in Table 2.

**Table 2. Top-3 clustering models**

	<b>EEV, 6</b>	<b>VVE, 2</b>	<b>EII, 4</b>
<b>BIC</b>	-320.909	-359.419	-363.891

(Source: Our determination)

To select the optimal model of Table 3, any model selection criterion can be applied: likelihood ratio, Bayesian Information Criterion (BIC), integrated complete-data likelihood (ICL) (Biernacki et al. 2000).

The maximized log-likelihood obtained by using a penalty from the number of model parameters gives the value of the BIC criterion. Then, the models are compared by varying the parameter values and the numbers of clusters. (Banfield & Raftery, 1993).

According to (Dasgupta and Raftery 1998; Fraley and Raftery 1998, Simdiankin et al. 2020), BIC is the most efficient, when dealing with model-based clustering. Mclust library in R implements BIC as the default one in choosing the best GMM.

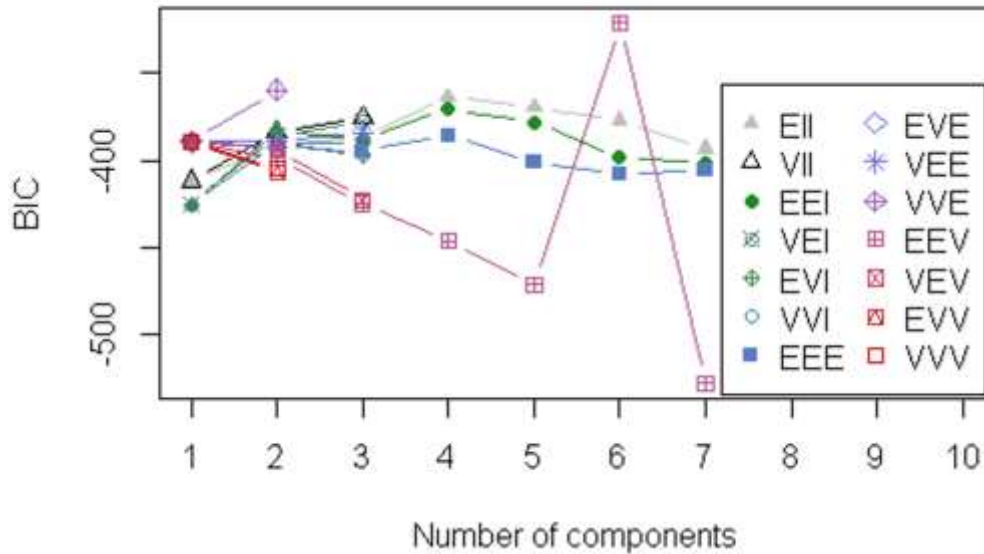
**Table 3. EVV clustering model**

<b>log-likelihood</b>	<b>n</b>	<b>df</b>	<b>BIC</b>	<b>ICL</b>
6.156	28	0	-320.909	-320.909

(Source: Our determination)

We chose the multivariate mixture model EEV (ellipsoidal, equal volume and equal shape) with 6 clusters, having the largest value of the BIC criterion -320.909, i.e. Mclust EEV (ellipsoidal, equal volume and shape) model, with 6 components, described in Table 3. Figure 1 presents various possible models, the corresponding BIC values, and the number of components.

Figure 1. Bayesian Information Criteria and the optimal number of clusters



(Source: Our determination)

On Ox axis the number of clusters is represented and on Oy axis the values of BIC criterion are represented. The highest peak of the graph determines the optimal number of clusters and the optimal GMM.

We apply dimension reduction for model-based on clustering and we obtain 5 dimensions with the structure. Estimated basis vectors (dimensions) are seen in Table 4.

Table 4. Dimensions of the clustering method

	Dir1	Dir2	Dir3	Dir4	Dir5
V1	-0.228	0.669	0.273	0.233	-0.734
V2	-0.761	-0.275	-0.739	0.350	0.009
V3	0.147	0.261	-0.147	0.445	0.427
V4	-0.541	-0.387	0.577	-0.671	0.527
V5	0.235	-0.509	0.155	0.417	0.021

(Source: Our determination)

Table 5 shows the eigenvalues of each dimension and shows that first 4 dimensions explain 99.99% of the total variance, i.e., the fifth dimension doesn't add value into the analysis.

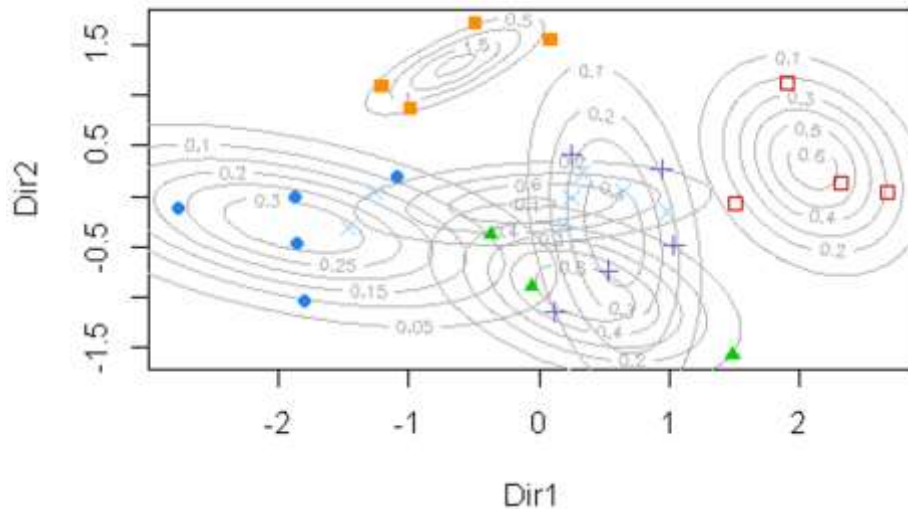
**Table 5. Eigenvalues and cumulative variance explained by dimensions**

	Dir1	Dir2	Dir3	Dir4	Dir5
Eigenvalues	1.2127	0.9362	0.6159	0.3002	0.0003
Cum. %	39.56	70.10	90.19	<b>99.99</b>	100.00

(Source: Our determination)

Figure 2 presents the clustering ellipses in the first two dimensions (Dir1 and Dir2).

**Figure 2. Elliptical Clusters**



(Source: Our determination)

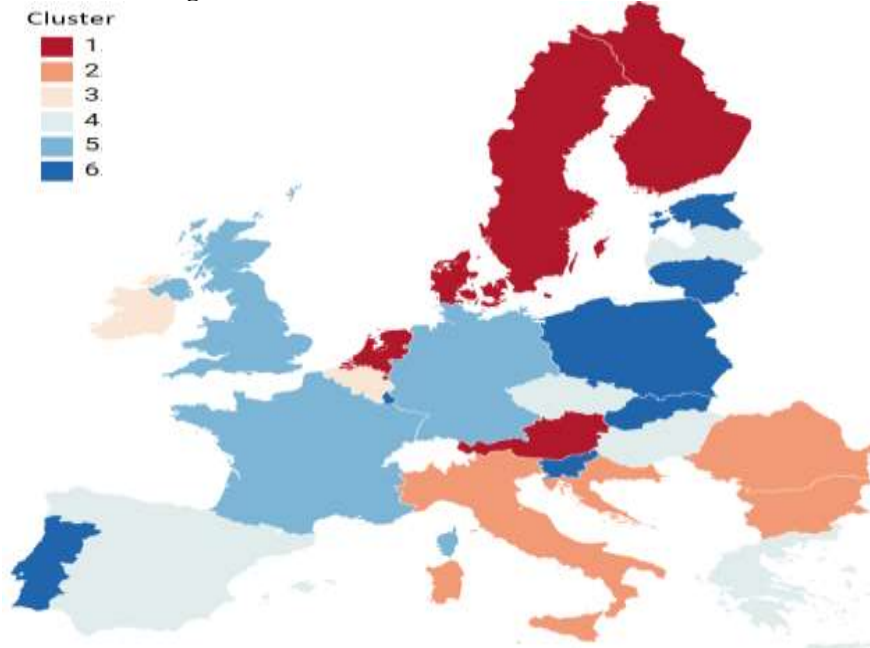
This method has been introduced by Lucca Scrucca (2015). Dimensions are linear combinations of the original variables, ordered by importance that is quantified by eigenvectors. These dimensions explain the cluster structure of the original data.

Figure 3 shows the clustering results on the European map. The cluster distribution is the following:

- Cluster 1: AUT, DNK, NDL, SWE, and FIN;
- Cluster 2: BGR, HRV, ITA, and ROU;
- Cluster 3: BEL, CYP, and IRL;
- Cluster 4: CZE, HUN, LVA, and ESP;
- Cluster 5: DEU, FRA, MLT, and GBR;
- Cluster 6: EST, LTU, LUX, POL, PRT, SVK, and SVN.



Figure 3. E-Government clusters of the EU states



(Source: Our determination)

Clusters 1-5 have 3-4 countries and cluster 6 is the largest. First cluster includes the Scandinavian countries (Denmark, Finland and Sweden) together Austria and Netherlands. Kinnunen et al. (2019) showed that these, specifically the Scandinavian countries, were on the top of the list of the most digitalized EU countries measured by digitalization of enterprises, workers and individuals included their use of e-government services Cseh Papp et al., 2018).

Similarly, the cluster two countries, and specifically, Bulgaria and Romania were found on the bottom of the list in most of the indicators.

Expectedly, the consumers of the most digitalized countries were digitally literate based on their use of product and price comparisons before their purchasing decisions, and less illiterate in less digitalized clusters, except, rather unintuitively, Romanian and Bulgarian online-shoppers showed the most digitally literate purchasing behavior. Now with our set of e-government features, we obtain one more clusters than in the above studies and, thus, the construction of the clusters is somewhat different.

Figure 4. Cluster averages of E-Government features



(Source: Our determination)

Figure 4 shows the cluster averages. The first 4 variable values are shown on the left-hand side, and for the last variable, the public R&D investments in ICT in millions of Euros are shown on the right-hand side (RHS). The bottom of the Figure 4 shows the averages for all 28 EU countries (AVG\_all) on the first number column, and for clusters 1-6 on the following columns. The first three variables, V1-V3 (telecommunication infrastructure, citizens' access to e-government services and Transparency international's Corruption Perception Index, PCI) have values between 0 and 100, V2 showing the % of citizens and the other two being indices. For the EU their averages are 69.1, 54.9% and 64.7, respectively (AVG\_all in Figure 4). The last two variables, V5 and V4 measure the relative and the absolute monetary amounts publicly invested to R&D in ICT sector. For the EU, the average %-share invested to R&D in ICT is 249.74 million Euros, which is 8.6% of the total R&D investments. The obtained 6 clusters are described as follows.

*Cluster 1* (AUT, DNK, NDL, SWE, and FIN) shows the largest, or almost largest, values for V1-V3 on average. The telecom infrastructure gets the index value of 77.1 and the CPI of 83.2 and 83.2% of the citizens have access to e-government services. These countries' public investments to R&D in ICT, on average, are 316.9 million Euros (9.6% of their total R&D investments). Denmark has the best infrastructure (V1), e-government service availability (V2), as well as, transparency of the administration, which compensate Denmark's lowest investments in R&D in ICT (166 mil. Eur and 6.2% of total R&D investments). Netherlands and Sweden have the largest absolute investments of 469 and 462 mil.

Eur, while Finland together with Sweden has the largest %-shares of the total investments, i.e. 12.4% and 12.6%, respectively.

*Cluster 2* (BGR, HRV, ITA, and ROU) show the lowest values of the 6 clusters for V1 (60.2), V2 (22.8) and V3 (47.3), while their public investment levels are not significantly under EU averages with their 215.2 mil. Eur investments to R&D in ICT and 7.5% share of their total investments. Access to e-government services and the transparency are the most problematic features. Only 22.8% of their citizens have access to public digital services; Croatia has the highest level of access (36%) and Romania has the lowest, only 9% of its citizens have access to e-government services. The corruption perception index ranges from the lowest (of all EU countries) Bulgaria's CPI=42 to Italy's CPI=52.

*Cluster 3* (BEL, CYP, and IRL) shows EU's average level infrastructure (V1=70.6) and transparency (V3=69) and almost EU-average availability of e-government services (50.7% of their citizens). Their public investments to R&D in ICT seem low by 140 mil. Eur, but it is 18.1% of their total R&D investments, the highest of the 6 clusters. Telecom infrastructure index doesn't vary within the cluster, it ranges from 69 to 71, access to e-government services is above 50% in other countries, but in Cyprus the access is available for 42%; similarly, the corruption index varies only from 69 to 75, while Cyprus shows a low CPI=59.

*Cluster 4* (CZE, HUN, LVA, and ESP) has the second weakest telecommunication infrastructure (V1=62.2) and transparency (V3=53.2) only after Cluster 2. 55.8% of citizens have access to e-government services, which is roughly the same as in clusters 5 and 6 and it is the average EU level. Highest variation is found in V5: Spain invests 523 mil. Eur to R&D in ICT, Czech Republic invests 127 mil. Eur, while Latvia only 8 mil. Eur. In relative terms, however, the shares of total R&D ranges from Greece's 7.05% to Latvia's 12.95%.

*Cluster 5* (DEU, FRA, MLT, and GBR) has the best telecommunications infrastructure (V1=79), while its e-government access ranges from Malta's low 47% to France's decent 71% and CPI from Malta's low 54 to Germany's and UK's good 80. In practice, Malta doesn't invest in R&D in ICT (363 thousand Euros, 1.4% of its all R&D investments), while Germany invests 1.8 billion Euros (5.9% of its total R&D investments), and France and UK invest 689 mil. Eur (4.9%) and 652 mil. Eur (6.7%), respectively.

*Cluster 6* (EST, LTU, LUX, POL, PRT, SVK, and SVN) is closest to the EU averages by V1-V3. The telecommunication infrastructure is the best in Luxembourg (V1=80) and Estonia (V1=76) and weakest in Poland (V1=58). Corruption perception index ranges from Slovakia's CPI=50, Lithuania's (59), Poland's (60) and Slovenia's (60) weak levels to Luxembourg's CPI=81. Access to e-government services ranges from Poland's and Portugal's 35% and 42%, respectively to Estonia's 79%. Public investments to R&D in ICT are the second lowest only after Cluster 5: the amounts range from Lithuania's 6 mil. Euros (4.3%) to Luxembourg's 57 mil. Euros (9.7% of total R&D investments).

### **3. Conclusions**

We applied the Gaussian Mixture Models to identify the optimal number of clusters of the 28 European Union countries after comparison of set of six different clustering models and determining the best model solve the clustering problem. The EU states were divided into 6 clusters based on their similarity by the five variables: 3 non-monetary features of their e-governmental environment, i.e. telecommunications infrastructure, citizens' access to e-government services, and the transparency/corruption of their public administrations, as well as, two monetary variables of euro-valued public investments to R&D in ICT sector and its relative %-share to their total R&D investments (Dečman, 2018).

We found that Cluster 1 of the Scandinavian countries plus Netherlands and Austria (AUT, DNK, NDL, SWE and FIN) showed the largest averages for the three variables: telecommunications infrastructure, individuals' access to e-government services and the transparency measured by the corruption perception index (CPI). Cluster 2 of Romania, Bulgaria, Italy and Croatia showed the lowest average values for the same variables. The results were in line with the earlier findings on general digitalization of these countries (Kinnunen et al., 2020; Afonasova et al., 2019; Zabala & Ślusarczyk, 2020). Cluster 4 (CZE, HUN, LVA, and ESP) was also seen problematic in terms of its level of telecommunication infrastructure, as well as, its level of corruption/transparency.

Cluster 5 of the largest EU countries plus Malta (DEU, FRA, MLT, BRD) had invested the largest monetary amounts to R&D in ICT sector, but the investments, in fact, were the smallest share of their total R&D investments, while Cluster 6 of the Eastern-European countries plus Portugal and Luxemburg (EST, LTU, LUX, POL, PRT, SVK, SVN) had invested the smallest absolute amounts, and second smallest relative amounts in R&D in ICT sector. Other European countries, Latvia (CL4), Malta (CL5), Slovakia and Slovenia (CL6), had the smallest public investments in R&D and ICT, only 8-12 mil. Euros.

Cluster 3 composed by relative small and rich countries (BEL, CYP, IRL) was close to the average EU levels by the non-monetary measures of telecommunication infrastructure, access to e-government services and transparency of their public administration, while showing roughly half of the EU average absolute amount invested to R&D, which in relative terms, was the largest share of total R&D investments in the EU area.

#### **Authors Contributions**

The authors listed have made a substantial, direct and intellectual contribution to the work, and approved it for publication.

#### **Conflict of Interest Statement**

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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