Adaptation of European Enterprises to COVID-19 Pandemic: Cluster Analysis Findings

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Abstract— The Covid 19 pandemic had a significant impact on every aspect of business and personal life. The use of digital technologies was an important lever in overcoming barriers that resulted from the need for physical distance. Businesses made greater use of various digital technologies such as electronic communications, remote use of computers in businesses, and online meetings. In addition, e-commerce has become the primary venue for selling products and services. However, differences between countries became apparent in the response to the Covid 19 pandemic. This paper aims to explore the digital divide between European countries based on their adaptation to the Covid 19 pandemic using a cluster analysis. The Eurostat database is used as a source for the variables measuring the response of firms to the Covid 19 pandemic in terms of communication tools and e-commerce usage. K-Means cluster analysis is used to analyze the homogeneity of countries based on the observed variables. Combined with the LSD post-hoc test, the Anova analysis compares clusters by GDP per capita. The results show that business agility is strongly associated with the country's economic development.

Keywords: Covid-19, pandemic, e-commerce, response, adaptation, Europe, cluster analysis, digital divide

I. Introduction

Numerous research papers have examined the impact of COVID -19 from a variety of perspectives and geographic locations. In the short term, for example, severe impacts on lost sales, business closures, mass layoffs, and liquidity have been documented in various countries [1]; [2]. The impact on businesses is multifaceted, with sluggish demand most often described as the biggest problem in recent business surveys and becoming more significant over time [3]. While there is considerable uncertainty about the long-term impact of the pandemic, evidence from previous crises suggests the possibility of lasting scarring effects. The impact of the shock on reallocation is expected to persist long after the Covid 19 epidemic has subsided [4]. according to estimates by [5], liquidity shortages occur for firms under various shock scenarios, regardless of age, size, or productivity. The uncertainty could further hamper economic activities. During this epidemic, unprecedented levels of uncertainty have been observed. Companies have been shown to respond by cutting spending on innovation and general management improvements, which is likely to affect future productivity development [6]. However, companies have responded to the crisis with digital transformation [7]; [8], which is already being deployed in various business areas such as human resources [9]; [10], education [11], and smart factories [12].

This paper analyzes the behavior of 23 European countries based on data collected by Eurostat. Variables include companies' remote access to their email system, information and communication technology (ICT) systems other than email systems, meetings, and platforms for selling goods or services. To complement the country comparison on a global level, an economic indicator, gross domestic product (GDP) per capita, was also used [13].

The study uses K-means clustering [14], which has been widely used to study the homogeneity of countries according to various indicators of technological development ([15]; [16]; [17]; [18]; [19]; [20]; [21]). Anova analysis is used to compare the mean values of variables between clusters. In similar studies, Anova analysis is applied to investigate the impact of digitalization, especially remote access in business environment [22]. In addition, an analysis is applied to examine the differences between clusters by GDP per capita, followed by a post-hoc Lease Significant Difference (LSD) test [23]; [24].

The article' is organized as follows: After a brief introduction in the first section, the methodology section details the research technique. The second section consists of the K-Means cluster analysis and the Anova comparison of the variables between the clusters. The third section examines the relationship between country clusters and GDP per capita. The final section provides the concluding observations, limitations, and recommendations for future research.

II. Methodology

A. Data Sources

The research variables come from the Eurostat database, shown in Table 1, which describes the use of remote access by companies in their daily work environment affected by the Covid 19 pandemic [25]. This study is concerned with four variables that measure the company's remote access to its email system (ENT1), access to ICT systems other than email systems (ENT2), remote meetings (ENT3), and use of online platforms for selling goods or services (ENT4). The dataset consists of 23 European countries, with 2021 being the first year after the Covid 19 pandemic. In addition, the variables are presented in Table 1 in the percentages of firms with at least 10 employees, where 2021 is the period studied. The GDP per capita (GDPpc.)

variable is also included and is expressed in U.S. dollar (USD) currency.

TABLE 1. RESEARCH VARIABLES, % OF ENTERPRISES WITH 10+ EMPLOYEES

Variable description	*Measurement*
ENT1. Companies with an increase in remote access to the company's email system due entirely to the Covid-19	% of enterprises; 10+ employees; year 2021
ENT2. Companies with an increase in remote access to company ICT systems other than email, which was entirely a consequence of the Covid-19	% of enterprises; 10+ employees; year 2021
ENT3. Companies with an increase in the number of remote meetings, which was entirely caused by the Covid-19	% of enterprises; 10+ employees; year 2021
ENT4. Due to the Covid-19, in 2020, the company started or increased its efforts to sell goods or services online.	% of enterprises; 10+ employees; year 2021
GDPpc. GDP per capita (USD)	USD per inhabitant; the year 2021

Source: Authors' work

Eurostat data measuring business-to-business processes and procedures with remote access (Table 2). The variable „Enterprises with an increase in the number of remote meetings exclusively due to the Covid 19 pandemic (ENT3)“ has the highest percentage in all countries studied. On the other hand, the variable „Companies with an increase in remote access to the company's email system that is exclusively due to the Covid 19 pandemic (ENT1)“ has the lowest percentage of the four variables in all countries in the sample.

TABLE 2. RESEARCH VARIABLES INCLUDED COUNTRIES AND GDP PER CAPITA DATA

Country	*ENT1.*	*ENT2.*	*ENT3.*	*ENT4.*	*GDPpc.*
Austria	21	22	43	19	53.268
Belgium	13	18	46	16	51.768
Bosnia and Herzegovina	7	5	12	11	6.917
Bulgaria	9	9	14	9	11.635
Croatia	7	10	26	8	17.399
Cyprus	17	16	31	23	30.798
Finland	12	13	48	17	53.983
Germany	15	15	30	5	50.802
Hungary	3	3	19	14	18.773
Italy	14	16	27	19	35.551
Latvia	8	9	19	10	20.642
Lithuania	6	7	24	10	23.433
Malta	23	28	38	32	33.257
Montenegro	8	9	20	14	9.367
Netherlands	15	17	48	17	58.061
Norway	5	7	57	12	89.203
Poland	10	14	23	6	17.841
Portugal	9	10	29	21	24.262
Serbia	11	10	21	10	9.215
Slovakia	8	11	19	11	21.088
Slovenia	6	8	28	7	29.201
Sweden	8	12	46	20	60.239
Turkey	9	7	10	14	9.587

Source: Authors' work

B. *Statistical analysis*

Data refer to firms with more than 10 employees, excluding the financial sector and accounting. To complement the country comparison at the global level, an economic indicator, gross domestic product (GDP) per capita, is also used. GDP is a good economic indicator for this research topic and can therefore be used as an efficient benchmark for the development of a given country in 2021 [26].

To classify the countries, a non-hierarchical statistical cluster analysis is performed. To obtain the initial centroids or estimates, the k-means grouping algorithm and the largest average distance technique are used [27]. After the variables are analyzed, they are assigned to the nearest centroid; new centroid coordinates are generated [28]. The Euclidean squared distance is used to calculate the distance between the center and the 'position of the variables on the map, in order to give more weight to the variables that are farther from the center of the map [29]. This grouping approach has been run a total of fifty times and aims to investigate the homogeneity of the dataset.

In addition to k-means clustering, the authors of this study use an Anova analysis, which is used to study the impact of digitization, especially remote access in the enterprise environment [30]. First, using Anova analysis [31], we compare the mean values of the observed variables that measure the response of countries' to covid pandemics in the different clusters. Second, we compare GDP per capita across clusters using Anova analysis and the LSD test. To examine the assumptions of the Anova analysis, the normality of the distribution of GDP per capita is tested. Also, the homogeneity of the variance of the same variable is examined when comparing the clusters.

All of this is preceded by an individual normalization of the variables using the built-in data normalization function in the Statistica statistical software used for this research analysis. Normalization involves translating the lowest and highest values of the analyzed variables into a predefined range, which increases the accuracy of the grouping algorithm and thus the quality of the clusters created [32]. There are several ways to determine the exact number of clusters, such as the rule of thumb [33], the elbow technique [34], cross-validation, the kernel matrix [35], or the information criterion approach [36]. In this study, we use the V-fold validation and the elbow technique to determine the optimal number of clusters.

III. DISCUSSION

A. *Cluster analysis*

Figure 1 shows a diagram of the cost sequence using the elbow rule method, which clearly shows that the best solution consists of a total of four clusters. The above diagram shows the error function for distinct cluster solutions [37], i.e., the average distance of observations in the subsamples from the assigned cluster centers. Differences in cluster costs or errors between solutions with two to three clusters are considered significant, i.e., errors decrease by more than 5% compared to a clustered solution with one fewer cluster as the number of clusters increases. The solution with four clusters is the best solution because the error difference between solutions with three or four clusters is less than 5%.

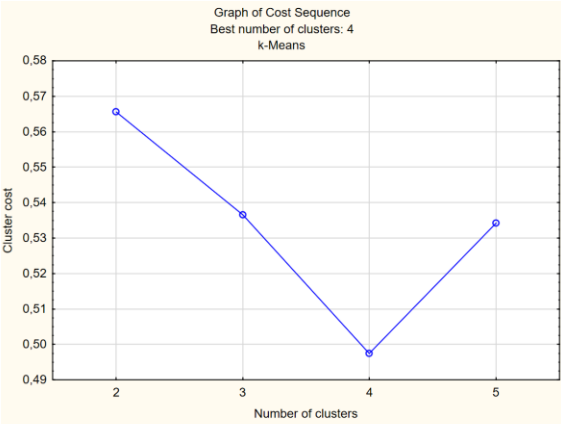

Figure 1. Graph of cost sequence; Source: Authors, Eurostat (2021)

Table 3 shows the results of the Anova analysis, which confirm that the means of the observed variables are statistically different between clusters at the 5% level, indicating that the four-cluster solution is appropriate (note: *** statistically significant below 1% probability).

TABLE 3. ANOVA ANALYSIS OF THE RESEARCH VARIABLES

Research variables	*Between SS*	*df*	*Within SS*	*df*	*F*	*p-value*
ENT1.	451.456	3	102.022	19	28.026	0.000***
ENT2.	587.495	3	136,5055	19	27.258	0.000***
ENT3.	2786.756	3	968.9835	19	18.214	0.000***
ENT4.	424.988	3	461.6209	19	5.831	0.009***

Source: Authors' work

The average values of the research variables by cluster are shown in Table 4. It can be seen that Cluster 1 and Cluster 3 contain the most countries in the research sample. Cluster 4 represents only one country (Norway) with an extremely high value (57%) of variable ENT3, which measures an increase in the number of remote sessions caused solely by the Covid 19 pandemic.

TABLE 4. AVERAGE VALUES OF OBSERVED VARIABLES BY CLUSTERS

Research variables	*C1*	*C2*	*C3*	*C4*
ENT1.	7.77	22.00	13.43	5.00
ENT2.	8.62	25.00	15.29	7.00
ENT3.	20.31	40.50	39.43	57.00
ENT4.	11.15	25.50	16.71	12.00
Number of countries	13	2	7	1
% share	56.52	8.70	30.43	4.35

Source: Authors' work

Table 5. shows the research variables of the countries by clusters together with the distance to the center of gravity.

TABLE 5. COUNTRIES BY CLUSTER AND DISTANCE FROM THE CENTROID

Country	*Cluster*	*Centroid distance*
Bulgaria	1	0.291
Latvia	1	0.097
Lithuania	1	0.274
Hungary	1	0.596
Poland	1	0.575
Portugal	1	0.667
Slovenia	1	0.431
Slovakia	1	0.140
Croatia	1	0.332
Montenegro	1	0.139
Serbia	1	0.274
Turkey	1	0.451
Bosnia and Hercegovina	1	0.366
Malta	2	0.464
Austria	2	0.464
Belgium	3	0.296
Germany	3	0.724
Italia	3	0.406
Cyprus	3	0.619
Netherlands	3	0.340
Finland	3	0.356
Sweden	3	0.664
Norway	4	0.000

Source: Authors' work

13 countries, including Bulgaria, Latvia, Lithuania, Hungary, Poland, Portugal, Slovenia, Slovakia, Croatia, Montenegro, Serbia, Turkey, and Bosnia and Herzegovina, fall under cluster 1. This cluster contains countries belonging to different geographical regions, such as Southeastern Europe (Bulgaria, Bosnia and Herzegovina, Serbia, Montenegro, the eastern part of Turkey), Southern Europe (Portugal), Central Europe (Slovenia, Hungary, Croatia, Poland, Slovakia), and Northern Europe (Latvia, Lithuania). Cluster 1 has the lowest average scores of all research variables compared to the other three clusters. The smallest differences between the countries in cluster 1 were observed for the variable ENT4.

Cluster 2 includes the following two countries: Malta and Austria. By geographic regions, Austria belongs to Central Europe, while Malta belongs to Southern Europe. Both regions fall under the economically developed regions of Europe and are members of the European Union. In contrast to all three other clusters, cluster 2 has the highest average values for the variables ENT1., ENT2. and ENT4, suggesting that the countries in cluster 2 have made the greatest technological progress due to the Covid 19 pandemic.

Cluster 3 includes the following countries: Belgium, Germany, Italy, Cyprus, the Netherlands, Finland, and Sweden. These countries belong to different geographic regions, such as Western Europe (Belgium, Netherlands), Central Europe (Germany), Southern Europe (Italy), Northern Europe (Finland, Sweden), and Southeastern Europe (Cyprus). Countries within this cluster scored the lowest averages for the variable ENT1 and the highest for the variable ENT3. In terms of shares in all variables, the countries in this cluster follow immediately behind Austria and Malta, which form cluster 2.

Cluster 4 contains only one country, Norway. This country is not a member of the European Union and belongs to the Nordic region in Northern Europe. This cluster is specific because it achieves the highest average score in the survey variable ENT3. As for the other three clusters, Norway achieves the lowest average value for the variable ENT1.

It is easy to see that the highest average value in all clusters was recorded for the variable ENT3. This can be easily explained by the fact that in all countries it was necessary to introduce social distancing to prevent the spread of infection. Thus, the physical holding of meetings was replaced by the holding of remote meetings precisely because of the outbreak of the pandemic. On the other hand, the smallest average values for all clusters are observed for the variable ENT1. Considering that the first free email services appeared in the 1990s, it can be assumed that most companies were already using email for their business before the Covid 19 pandemic and that their use is only partly due to the occurrence of the Covid 19 pandemic.

Figure 2. shows the countries included in the clusters. The only country shown is Norway, which represents cluster 4.

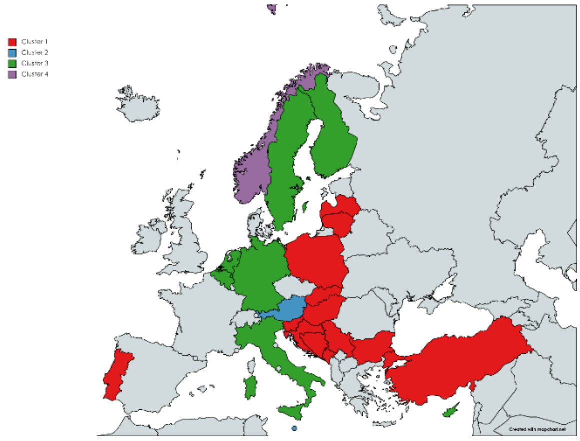

Figure 2. Countries across clusters on the Europe map; Source: Authors, Eurostat (2021); https://mapchart.net/

Table 6. shows the Pearson correlation matrix for the four observed variables. It can be seen that none of the research variables have a higher correlation than 0.7 between the variables included in the data set. The only variables with a higher correlation are variables 1 and 2, and variable 3 and GDP per capita.

TABLE 6. PEARSON CORRELATION MATRIX OF RESEARCH VARIABLES AND GDP PER CAPITA (THE YEAR 2021, USD)

	ENT1.	*ENT2.*	*ENT3.*	*ENT4.*	*GDPpc.*
ENT1.	1	0.940	0.363	0.613	0.260
ENT2.		1	0.496	0.619	0.363
ENT3			1	0.408	0.938
ENT4.				1	0.249
GDPpc.					1

Source: Authors' work

To investigate the relationship between business adaptation to the economy and changes in business methods and procedures and the level of economic growth of selected European countries for the year 2021, we estimated the average values of GDP per capita for each defined cluster. The results of the examined correlations are presented in Table 7. Cluster 4, which consisted only of Norway, achieves the highest average GDP per capita (89,202.80 USD), which was expected considering that Norway has the highest GDP per capita in Europe after Luxembourg, Ireland, and Switzerland [38]. The lowest average GDP per capita is found in cluster 1, which includes the countries of the Western Balkans and the Baltic countries, which, according to [38], are at the bottom of the list of European countries in terms of GDP per capita achieved in 2021.

TABLE 7. GDP PER CAPITA IN 2021 BY CLUSTERS

Cluster	*Average GDP per capita (USD)*	*Number of countries*	*St. Dev.*
C1	16.873,75	13	6.95853
C2	43.262,65	2	14.14956
C3	48.743,14	7	11.22386
C4	89.202,80	1	-
Total	32.012,56	23	21.31979

Source: Authors' work

Figure 3 shows the average value of GDP per capita per cluster. Cluster 4 has the highest value of $89,203, while the lowest value for cluster 1 is $ 16,874.

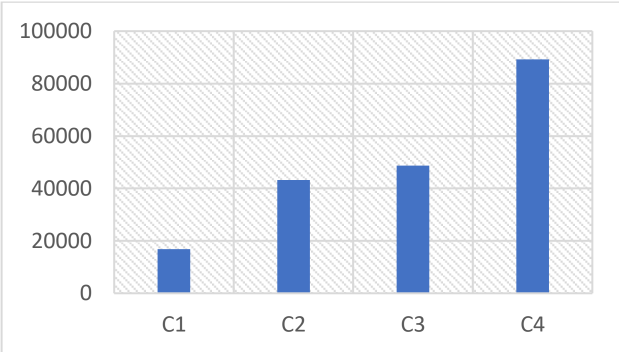

Figure 3. Average values of GDP per capita according to clusters; Source: Authors, Eurostat (2021)

Table 8. shows the results of the Kolmogorov-Smirnov normality test for the distribution of the GDP per capita variable, and the results show that the distribution of GDP per capita follows a normal distribution. Where in a. the normal distribution is tested, in b. the indicators are calculated based on the sample, and in c. the Liliefors correction was used.

TABLE 8. KOLMOGOROV-SMIRNOV TEST OF NORMALITY OF THE DISTRIBUTION OF THE GDP PER CAPITA VARIABLE

One-Sample Kolmogorov-Smirnov Test	*GDP_per_capita*
N	22
Normal Parameters (Mean)[a]	29413.004
Normal Parameters (Std. Deviation)[b]	9223.372
Test Statistic	0.160
Asymp. Sig. (2-tailed)[c]	0.148

Table 9. shows the Levene homogeneity test of the variance of the GDP per capita variable. The test result shows that the assumption of homogeneity of the variance of the GDP per capita variable cannot be rejected.

TABLE 9. LEVENE HOMOGENEITY TEST OF THE VARIANCE OF THE GDP PER CAPITA VARIABLE

Tests of Homogeneity of Variances	*Levene Statistic*	*df1*	*df2*	*Sig.*
GDP_per_capita	1.688	2	19	0.211

Source: Authors' work

The Anova analysis presented in Table 10 shows that the differences in the average values of GDP per capita of the identified clusters are statistically significant, indicating a strong correlation between economic growth and digital transformation in the European countries studied.

TABLE 10. RESULTS OF ANOVA ANALYSIS OF GDP PER CAPITA DIFFERENCES BY CLUSTERS

	Sum of Squares	*df*	*Mean Square*	*F*	*Sig.*
Between Groups	5.04E+09	2	2.5216E+09	31.169	0.000***
Within Groups	1.54E+09	19	8.0901E+07		
Total	6.58E+09	21			

Source: Authors' work; Note: *** statistically significant under 1% probability).

Anova analysis indicates a difference between at least two groups of the observed variable, but does not indicate which groups are statistically significantly different. To test this assumption, a post-hoc LSD analysis is performed. Table 11. shows the post-hoc analysis of GDP per capita between clusters. All clusters show a significant relationship with probability less than 1%, except for the relationship between cluster 2 and cluster 3, and between cluster 3 and cluster 1 (

TABLE 11. POST-HOC LSD ANALYSIS OF THE DIFFERENCE IN GDP PER CAPITA BY CLUSTERS

(I) Cluster	*(J) Cluster*	*Mean Difference (I-J)*	*Std. Error*	*Sig.*
C1	C2	-26388,896	6831,803	0,001***
	C3	-31869,389	4216,681	0,000***
C2	C1	26388,896	6831,803	0,001***
	C3	-5480,493	7211,633	0,457
C3	C1	31869,389	4216,681	0,000***
	C2	5480,493	7211,633	0,457

Source: Authors' work; Note: *** statistically significant under 1% probability).

IV. CONCLUSION

An analysis of the homogeneity of European countries in terms of their adaptation to the changes in business methods and procedures triggered by the Covid 19 pandemic was performed, using non-hierarchical cluster analysis. Using the elbow rule, four clusters were defined as the best fit, which was also tested by an Anova analysis that confirmed the selection of the four defined clusters. Cluster 1 included the following countries: Bulgaria, Latvia, Lithuania, Hungary, Poland, Portugal, Slovenia, Slovakia, Croatia, Montenegro, Serbia, Turkey, and Bosnia and Herzegovina; cluster 2 included Malta and Austria; cluster 3 included Belgium, Germany, Italy, Cyprus, the Netherlands, Finland, and Sweden; and cluster 4 included Norway. All clusters had the highest number of companies that increased the number of remote meetings due to the Covid 19 pandemic, which can be explained by the introduction of social distancing as a method to prevent the spread of the Covid 19 pandemic. The correlation analysis showed the highest positive correlation between companies with an increase in remote access to the company's email system, which was solely a result of the Covid 19 pandemic, and companies with an increase in remote access to the company's ICT systems other than email, which was solely a result of the Covid 19 pandemic.

Similarly, although to a somewhat lesser extent, a strong positive correlation was found between firms that started selling goods or services online or increased their efforts during the pandemic and GDP per capita. Other correlations of the variables are statistically significant and indicate a moderate to good relationship between them. When examining the relationship between business adaptation and changes in business methods and procedures and the level of economic growth of selected European countries for 2021, the estimated average value of GDP per capita was highest in the fourth cluster, i.e. Norway, and lowest in the countries of the Western Balkans and Baltic countries, which are classified in cluster 1. The Anova analysis conducted further showed that there is a strong correlation between economic growth and digital transformation in the European countries studied.

The results of the cluster analysis confirmed significant differences among European countries in terms of business adaptation to the economy and changes in business methods and procedures as a result of the Covid 19 pandemic. In addition, the Anova analysis confirmed a strong relationship between economic growth and digital transformation in the European countries studied, suggesting that more developed countries have adapted more quickly to the Covid 19 pandemic. Since this research is based on only one year's data analysis, this analysis should be repeated for a longer period of time to confirm the obtained results, which also defines the limitation of the conducted analysis.

V. REFERENCES

[1] J.E. Humphries, C. Neilson, and G. Ulyssea, "The Evolving Impacts of COVID-19 on Small Businesses Since the CARES Act.," Cowles Foundation Discussion Papers 2230, April 2020.

[2] A. Adams-Prassl, T. Boneva, M. Golin, and C. Rauh, "Inequality in the impact of the coronavirus shock: Evidence from real time surveys," Journal of Public Economics, vol. 189, 104245, September 2020.

[3] O. A. Younes, and S. Altug, "The COVID-19 Shock: A Bayesian Approach," Journal of Risk and Financial Management, vol. 14, issue 10, 495, October 2021.

[4] D. Christelis, D. Georgarakos, T. Jappelli, and G. Kenny,"The COVID-19 Crisis and Consumption: Survey Evidence from Six EU Countries", SSRN Electronic Journal 3751097, December 2020.

[5] E. Bosio, S. Djankov, E. L. Glaeser, and A. Shleifer, "Public Procurement in Law and Practice," SSRN Electronic Journal, vol. 122, issue 4, pp. 1091-1117, May 2022.

[6] SA Tabish, "Covid-19 Pandemic: Emerging Perspectives and Future Trends," Journal of Public Health Research, vol. 9, issue 1, June 2020.

[7] J. Hunady, P. Pisár, D.S. Vugec, and M.P. Bach, "Digital Transformation in European Union: North is leading, and South is lagging behind," International Journal of Information Systems and Project Management, vol. 10, issue 4, pp. 58-81, November 2022.

[8] M. Tomičić Furjan, K. Tomičić-Pupek, and I. Pihir, "Understanding digital transformation initiatives: Case studies analysis," Business Systems Research: International journal of the Society for Advancing Innovation and Research in Economy, vol. 11, issue 1, pp. 125-141, 2020.

[9] A.F. Barišić, J.R., Barišić, and I. Miloloža, "Digital transformation: challenges for human resources management," ENTRENOVA-

ENTerprise REsearch InNOVAtion, vol. 7, issue 1, pp. 357-366, March 2022.
[10] A. Trubetskaya, and H. Mullers, “Transforming a global human resource service delivery operating model using Lean Six Sigma,” International Journal of Engineering Business Management, vol. 13, November 2021.
[11] I. Pavić, V. Mijušković, and I. Žager, “Which Digital Tools dominate Secondary and Higher Education in Economics: Google, Microsoft or Zoom?,” Business Systems Research: International Journal of the Society for Advancing Innovation and Research in Economy, vol. 13, issue 2, pp. 117-134, December, 2022.
[12] A. Jerman, A. Bertoncelj, and I. Erenda, “The influence of critical factors on business model at a smart factory: A case study,” Business Systems Research: International journal of the Society for Advancing Innovation and Research in Economy, vol. 10, issue 1, pp. 42-52, April 2019.
[13] A. Ishnazarov, N. Kasimova, S. Tosheva, and A. Isaeva, “ICT and Economic Growth: Evidence from Cross-Country Growth Modeling,” The 5th International Conference on Future Networks Amp Distributed Systems , pp. 668-671, December 2021.
[14] M. Ahmed, R. Seraj, and S. M. S. Islam, “The k-means Algorithm: A Comprehensive Survey and Performance Evaluation,” Electronics, vol. 9, issue 8, p. 1295, August 2020.
[15] M. Pejić Bach, J. Zoroja, and M. Loupis, “RFID usage in European enterprises and its relation to competitiveness: Cluster analysis approach,” International Journal of Engineering Business Management, vol. 8, December 2016.
[16] J. Zoroja, and M. Pejić Bach, “Impact of information and communication technology to the competitiveness of European countries-cluster analysis approach,” Journal of theoretical and applied electronic commerce research, vol. 11, issue 1, pp. 1-10, January 2016.
[17] A. Buljan, M. Spremić, “Cluster Analysis of IT Security Risks in Chosen Sectors,” ENTRENOVA-ENTerprise REsearch InNOVAtion, vol. 5, issue 1, pp. 489-496, September 2019.
[18] M. Pejić Bach, K. Dumičić, B. Žmuk, A. Bartolić, J. Zoroja, “Use of hierarchical clusters analysis in identification of obstacles to introduction of e-commerce in European countries”, IEEE, 42nd International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO), pp. 1325-1330, July 2019.
[19] M. Pejić Bach, T. Bertoncel, M. Meško, D. Suša Vugec, and L. Ivančić, “Big data usage in European countries: Cluster analysis approach”, Data, vol. 5, session 1, 25, March 2020.
[20] M. Pejić Bach, J. Zoroja, and I. Strugar, “Investment of European enterprises in ICT education of their employees: Relationship with country competitiveness and digital economy development,” IEEE, 43rd International Convention on Information, Communication and Electronic Technology (MIPRO), pp. 658-663, November 2020.
[21] B. Jaković, T. Ćurlin, I. Miloloža, “Enterprise digital divide: website e-commerce functionalities among European Union Enterprises,” Business Systems Research: International journal of the Society for Advancing Innovation and Research in Economy, vol. 12, issue 1, pp. 197-215, June 2021.
[22] S. Donati, G. Viola, F. Toscano, and S. Zappalà, (2021). “Not All Remote Workers Are Similar: Technology Acceptance, Remote Work Beliefs, and Wellbeing of Remote Workers during the Second Wave of the COVID-19 Pandemic,” International Journal of Environmental Research and Public Health, vol. 18, issue 22, p. 12095, January 2021.
[23] A. L. Scutariu, T. Șușu, C.E. Huidumac-Petrescu, and R.M. Gogonea (2021). “A Cluster Analysis Concerning the Behavior of Enterprises with E-Commerce Activity in the Context of the COVID-19 Pandemic,” Journal of Theoretical and Applied Electronic Commerce Research, vol. 17, issue 1, pp. 47–68, March 2022.
[24] T. Alberti, and D. Faranda, “On the uncertainty of real-time predictions of epidemic growths: A COVID-19 case study for China and Italy,” Communications in Nonlinear Science and Numerical Simulation, 90, p. 105372, November 2020.
[25] Eurostat, Covid-19 Impact on ICT usage by NACE Rev.2 activity (2022), Available at: https://ec.europa.eu/eurostat/databrowser/view/isoc_e_cvdn2/default/table?lang=en
[26] E. Battisti, S. Alfiero, E., and E. Leonidou, “Remote working and digital transformation during the COVID-19 pandemic: Economic–financial impacts and psychological drivers for employees” Journal of Business Research, 150, pp. 38–50, November 2022.
[27] A. Leogrande, “k-Means Clusterization and Machine Learning Prediction of European Most Cited Scientific Publications”, SSRN, 4195846, August 2022.
[28] D. Yu, X. Zhou, Y. Pan, Z. Niu, and H. Sun, “Application of Statistical K-Means Algorithm for University Academic Evaluation”, Entropy, vol. 24, issue 7, 1004, 2022.
[29] M. Faisal, E. M., Zamzami, and Sutarman “Comparative Analysis of Inter-Centroid K-Means Performance using Euclidean Distance, Canberra Distance and Manhattan Distance”, Journal of Physics: Conference Series, vol. 1566, issue 1, p. 012112, June 2020.
[30] S. Kalogiannidis, D. Kalfas, F. Chatzitheodoridis, and S. Kontsas, “The Impact of Digitalization in Supporting the Performance of Circular Economy: A Case Study of Greece, ” Journal of Risk and Financial Management, vol. 15, issue 8, 349, August 2022.
[31] M. Garaus, and C. Garaus, “The Impact of the Covid-19 Pandemic on Consumers’ Intention to Use Shared-Mobility Services in German Cities,” Frontiers in Psychology, vol. 12, 646593, March 2021.
[32] I. B. Mohamad, and D. Usman, “Standardization and Its Effects on K-Means Clustering Algorithm,” Research Journal of Applied Sciences, Engineering and Technology, vol. 6, issue 17, pp. 3299–3303, September 2013.
[33] F. M. L. Di Lascio, D. Giammusso, and G. Puccetti,”A Clustering Approach and a Rule of Thumb for Risk Aggregation,” Journal of Banking & Finance, vol. 96, pp. 236-248, July 2018.
[34] E. Umargono, J. E. Suseno, and S. Vincensius Gunawan, “K-Means Clustering Optimization Using the Elbow Method and Early Centroid Determination Based on Mean and Median Formula,” Proceedings of the 2nd International Seminar on Science and Technology (ISSTEC 2019), Atlantis Press, pp. 121-129, 2020.
[35] N. Tsapanos, A. Tefas, N. Nikolaidis, and I. Pitas, “Kernel matrix trimming for improved Kernel K-means clustering,” IEEE International Conference on Image Processing (ICIP), pp. 2285-2289, 2015
[36] C. A. Sugar, and G. M. James, “Finding the Number of Clusters in a Dataset,” Journal of the American Statistical Association, vol. 98, issue 463, pp. 750–763.
[37] R. Tibshirani, G. Walther, and T. Hastie, “Estimating the number of clusters in a data set via the gap statistic,” Journal of the Royal Statistical Society: Series B (Statistical Methodology), vol. 63, issue 2, pp. 411–423, November 2000.
[38] Statistics Explained. (n.d.). https://ec.europa.eu/eurostat/statistics-explained/index.php?title=GDP_per_capita,_consumption_per_capita_and_price_level_indices