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The Influence of COVID-19 Phenomenon on the Labour Market at the European Regional Level

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Abstract. *The COVID-19 pandemic resulted in substantial job losses and an economic decline in European labour markets, with various effects observed at regional level. The unemployment rate experienced a sharp increase, disproportionately impacting the younger generation and individuals with limited skills. The prevalence of remote work has risen, creating difficulties in maintaining a healthy work-life balance. The three research questions concern: (1) examining scientific literature; (2) validating the effects of COVID-19 on the labour market; and (3) identifying the indicators and regions in Europe that have been most significantly affected. The study begins by performing an exploratory analysis of the data, then proceeds to an examination of the principal components to reduce dimensionality. It concludes with a cluster analysis to enhance the visualisation of different regions. The results are in conformity with the scientific literature but also indicate specificities for different regions or indicators. While most studies concentrate on examining the effects of this phenomenon on just a couple of European countries, the present research extensively analyses all regions across the continent. Furthermore, the study spans a prolonged period from 2018 to 2022, covering the period preceding the pandemic, the crisis itself, and the aftermath. The final contribution regards the methodology used, which considers both approaches utilised in the research.*

Keywords: COVID-19 epidemic, labour market, principal component analysis, cluster analysis, regions in Europe.

Introduction

The COVID-19 epidemic has caused remarkable disruptions in different sectors worldwide, with significant consequences for the labour market.

The present study aims to augment the existing academic research on the effects of COVID-19 on the labour market in European areas. Additionally, the paper aims to confirm this impact and identify the indicators and territories that were most impacted by this event.

The research submitted by Wang et al. introduces a causal path diagram that investigates the impact of government epidemic prevention measures on human mobility behaviours. The implementation of policies including school closures, public transport shutdowns, stay-at-home requirements, international travel restrictions, and vaccination regulations resulted in reduced mobility and hence contributed to a decrease in the projected number of ill or died individuals. (Wang et al., 2022).

Within this context the general objective of this study is to provide an in-depth and comprehensive examination of the influence that COVID-19 has had on the labour market in Europe. This review aims to improve comprehension of the problems and opportunities resulting from the pandemic's impact on Europe's labour market dynamics by consolidating previous research results and identifying significant patterns and insights. This study attempts to clarify the

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intricate interplay of factors that are shaping the evolving labour and employment landscape in Europe under the ongoing COVID-19 crisis.

Literature review

Prior studies in this area highlighted the diversity of effects based on the national context. An investigation based on principal component analysis showed that Greece encountered the lowest impact, meanwhile Netherlands dealt with the highest effect (Ertaş & EkiNci, 2022).

Previous research has shown the impact of the COVID-19 pandemic on the unemployment rate (Lambovska et al., 2021).

Research on employment market difficulties revealed a notable variation in the impact of the COVID-19 epidemic. Furthermore, the recovery following this shock showed varying patterns, with the pandemic having a long-lasting effect on unemployment levels (Mkiyes, 2021).

Furthermore, the COVID-19 pandemic has unequally affected individuals in the labour market based on demographic characteristics and industry background (Celbiş et al., 2023).

Certain demographic groups experienced worse labour market outcomes during pandemic (Béland et al., 2023).

Other factors explaining the variation in the impact of COVID-19 crises are given by different degrees of labour market development. Previous findings indicated that nations with the most favorable and unfavorable labour market conditions were grouped together in the same clusters. The COVID-19 pandemic has underscored the necessity for economies to adjust to technological advances and enhance digital competencies to establish a labour market that is more efficient and adaptable (Bieszk-Stolorz & Dmytrów, 2022).

Social distancing policies also impacted job losses, working hours and earnings (Gupta et al., 2023).

This research intends to investigate the variability within each country at a regional level, a topic that has not been previously addressed.

Methodology

The block diagram provided below illustrates the sequential steps conducted in the current study.

The starting point involved the conceptualization stage, which served as the motivating factor for this research. During this stage, the research questions and hypotheses to be explored were selected. The next step involved examining the accessibility of data along with other pertinent publications related to this subject. In the current situation, the verdict was favorable, allowing me to continue with the review of the specialised literature, verifying, collecting, cleaning, and structuring the data. If the outcome was detrimental, the plan of action involved revising the conceptualization phase. The following step consisted of choosing a methodology that matches the subject issue and providing crucial information. Afterwards, the analysis of the data took place, using the techniques mentioned in the methodology stage. During the last phase, the results were analysed and evaluated, contributing to the formulation of conclusions relating to the study. This, consequently, facilitated the starting point of discussions relevant to future research.

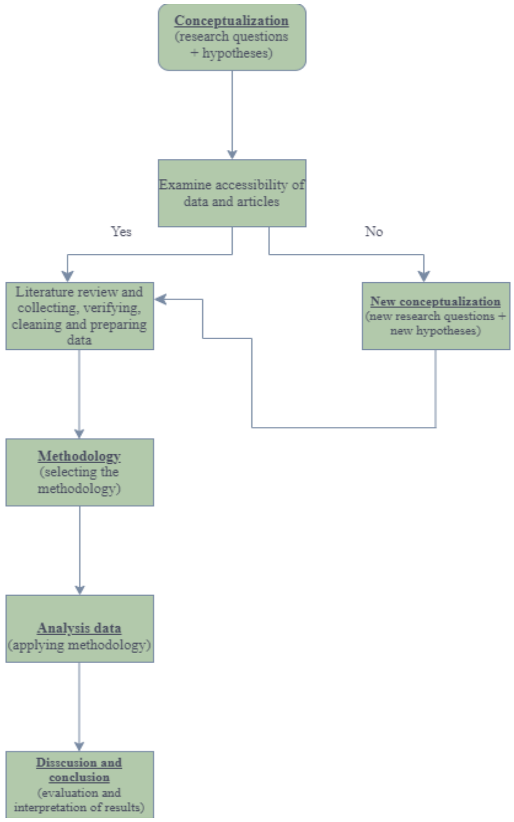

Figure 1. Conceptual framework diagram

Source: Author's own research.

The present research applies two techniques: principal component analysis and cluster analysis. Principal component analysis (PCA) is a technique for reducing the dimensionality of massive data sets. It accomplishes this by transforming a collection of variables into a smaller set that retains most of the information in the original data.

The first step involved data collection. The next step involved data preprocessing, including data cleansing, standardisation, and formatting. The next stage was to select the number of principal components. This decision can be based on the cumulative explained variance, aiming to retain a certain percentage (e.g., 70%, 80%, or 90%) of the total variance. The final decision was based on the Kaiser rule, which requires the removal of all components that possess eigenvalues lower than 1. The final step involved creating a visual representation of the results.

Cluster analysis is a technique of data analysis that investigates the inherent groups that exist in a data set, referred to as clusters. Cluster analysis is an unsupervised learning method that does not require dividing data points into established groups.

To summarize, the first step of this method involved establishing the objectives of the analysis. The next step was collecting and organising the data. The following step consisted of selecting the most suitable clustering algorithm and determining the appropriate number of clusters. Ultimately, the final phase was to create a visual representation.

Previous works using a similar methodology exist (Mogoș et al., 2022; Zamfir & Iordache, 2021). The main contribution of the present study comes from using regional data.

The software programmes utilised for collecting data, processing, and analysing it in the paper were Microsoft Excel and R.

Results and discussions

Exploratory data analysis

The data used in the analysis was obtained from Eurostat and contained the next set of indicators with their respective measurement units: Population (thousand persons), Employment rate (%), Average number of usual weekly hours of work in main job (hours), Long-term unemployment (%) and Employment in technology and knowledge-intensive sectors (percentage of total employment). The following table contains the indicators and their corresponding codes.

Table 1. Variable code and variable name of indicators

Variable code	Variable name
X_1	Population
X_2	Employment rate
X_3	Average number of usual weekly hours of work in main job
X_4	Long-term unemployment
X_5	Employment in technology and knowledge-intensive sectors

Source: Author's own research.

The selection of variables considered includes variables that have a direct effect on the labour market, such as long-term unemployment and the employment rate. Additionally, as shown, variables were included to provide a novel perspective, such as average working hours and employment in technology and knowledge-intensive sectors. In literature, COVID-19 emphasized the need for the economy to change to accommodate technology, and restrictions had a significant impact on average work hours. Thus, these types of variables were included in the paper.

It is important to note that several of the initial indicators used in the research had to be excluded since they contained redundant information, as noted in the establishment of the first correlation matrices.

The table below displays the overall number of regions for each specific year. Various factors contribute to the discrepancy in the number, including regions of Turkey no longer being part of Europe, lacking details in certain areas, or missing data.

Table 2. Distribution of regions by year

Year	Total regions
2018	329
2019	329
2020	288
2021	259
2022	259

Source: Author's own research.

The data examination part began with the creation of a line graph for each indicator, covering all the years within the analysis, to observe the change over time. The evolution over time has been calculated from the mean of all European regions. Furthermore, the data was analysed with attention to the first case of COVID-19 documented in Europe, exactly on January 24, 2020, in Bordeaux, France.

The following two graphs were used to analyse the indicators that showed the biggest disparities.

During the initial two years of the analysis, there was an apparent increase in the employment rate. Afterwards, there was a significant decline of around 2.75 percentage points caused by the initial outbreak of the pandemic. Setting off in 2021, the economy saw an improvement in the employment rate. The study conducted by Cohen aligns with the findings derived from the research (Cohen, 2020).

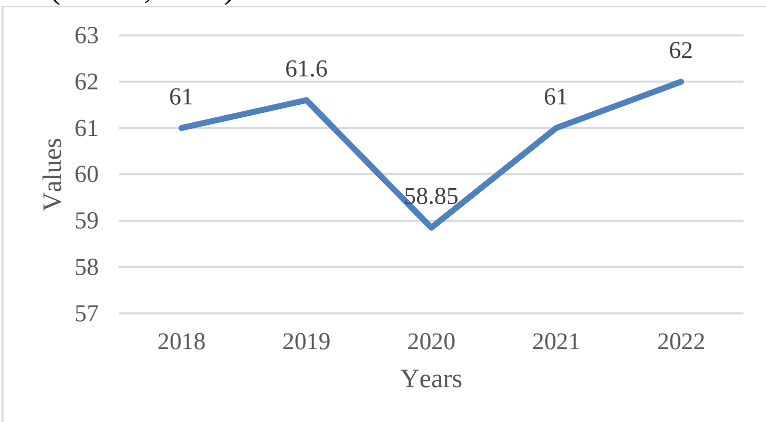

Figure 2. The evolution of the employment rate over time

Source: Author's own research.

The highest average number of hours worked was documented in 2020, coinciding with the year of the first lockdown. After that, in 2021, there was a drop of around 0.3 percentage points. The paper titled "Work-Life Conflict During the COVID-19 Pandemic" is highly relevant to this indicator analysis (Schieman et al., 2021).

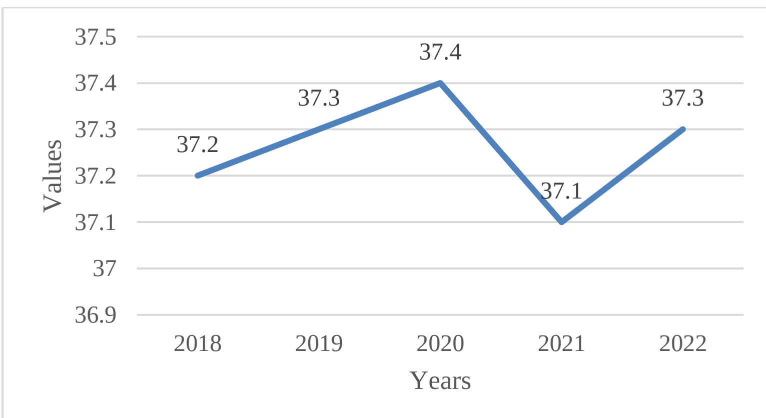

Figure 3. The evolution over time of the average hours worked in main job

Source: Author's own research.

The population's evolution over the analysed period is displayed in Figure 10 in the appendix. It is noticeable that the highest value was seen in 2019, followed by a subsequent decrease in the trend. Simultaneously, it is evident that the decline started precisely in 2020 upon the appearance of the first infection case. The studies validate the hypothesis that depopulation is a contributing factor to the formation of COVID-19 (Harper, 2021).

Figure 11 in the appendix displays the evolution of long-term unemployment over time. In 2020, there was an important reduction of nearly 2.9 percentage points in long-term unemployment. The percentage increased from 30% in 2020 to 33.4% in 2021, partly because of the ongoing pandemic. The Gezici and Ozay publications serve as comprehensive resources on this subject (Gezici & Ozay, 2020).

Figure 12 in the appendix illustrates the evolution over time of employment in technology and knowledge-intensive sectors. An upward trend is observed in the employment indicator within the technology and knowledge-intensive sectors when analysing data from the year 2020 onwards. The topic of digitalization is intriguing and highly relevant during this period (Amankwah-Amoah et al., 2021).

The table below presents the descriptive data and distribution type of the indicators for the period 2018–2022. Across the analysed years, the skewness coefficient indicates a to-the-right asymmetry for indicators population, average number of usual weekly hours of work in main job, Long-term unemployment, and Employment in technology and knowledge-intensive sectors. The employment rate indicator indicates a left asymmetry. The study revealed that all indicators examined for the whole period displayed a leptokurtic distribution.

Table 3. Descriptive statistics and distribution type of indicators

Year	Variables	X1	X2	X3	X4	X5
2018	Minimum value	17.8	31.4	28.9	10.3	0.2
	First quartile	568.2	54.6	36.2	25.7	2.1
	Median	954.4	61	37.2	37	3.1
	Mean	1205.5	59.76	37.94	37.73	3.494
	Third quartile	1482.6	66.4	39.8	45.8	4.6
	Maximum value	10764.7	79.6	51.5	81.8	10.9
	Skewness	3.73	-0.65	0.7	0.64	1
	Kurtosis	25.91	3.13	4.07	3.07	3.97
2019	Minimum value	17.4	30.9	29.3	10.2	0.1
	First quartile	561.6	54.5	36.1	24.6	2.2
	Median	949.9	61.6	37.3	32.9	3.3
	Mean	1205.6	60.11	37.92	35.31	3.674
	Third quartile	1494.2	66.8	39.8	42.7	4.8
	Maximum value	10816.4	78.4	52.8	84.4	11.9
	Skewness	3.74	-0.67	0.71	0.97	0.97
	Kurtosis	26.01	3.09	4.43	3.71	4.06
2020	Minimum value	18.1	26.7	29.3	3.2	0.1
	First quartile	555	52.25	36.17	23.27	2.2
	Median	933.8	58.85	37.4	30	3.4
	Mean	1231.9	58.02	37.94	33.38	3.827
	Third quartile	1501.1	64.72	39.9	39.58	5.1
	Maximum value	10883.7	77.1	51	83.9	12.9
	Skewness	3.59	-0.6	0.38	1.03	0.97
	Kurtosis	23.79	3.18	3.76	3.95	3.91

Year	Variables	X1	X2	X3	X4	X5
2021	Minimum value	17.8	35.8	29.8	15.6	0.6
	First quartile	537.6	55.45	35.45	25.8	2.6
	Median	885.2	61	37.1	33.4	3.7
	Mean	1142.9	60.07	37.28	35.75	4.24
	Third quartile	1383.3	65.8	39.45	42.75	5.25
	Maximum value	7918	75.4	47	79	13.7
	Skewness	2.78	-0.57	0.11	0.86	1.27
	Kurtosis	14.55	3.12	3.54	3.27	4.79
2022	Minimum value	16.3	36.9	29.8	9.5	0.5
	First quartile	531.1	56.5	35.4	24.5	2.5
	Median	877	62	37.3	33.4	3.8
	Mean	1143.2	61.38	37.26	34.96	4.339
	Third quartile	1364	66.9	39.45	42.75	5.5
	Maximum value	7952.5	77.1	46.3	81.2	13.5
	Skewness	2.78	-0.56	0.02	0.71	1.14
	Kurtosis	14.56	3.15	3.26	3.18	4.16

Source: Author's own research.

Principal component analysis

In the correlation matrix for 2018, a moderate negative correlation of -0.56 exists between the employment rate and the average number of usual weekly hours of work in main job. There is a moderate positive correlation of 0.54 between the employment rate and employment in technology and knowledge-intensive sectors. The correlation matrices for the remaining years analysed are displayed in figures 13, 14, 15, and 16 in the appendix.

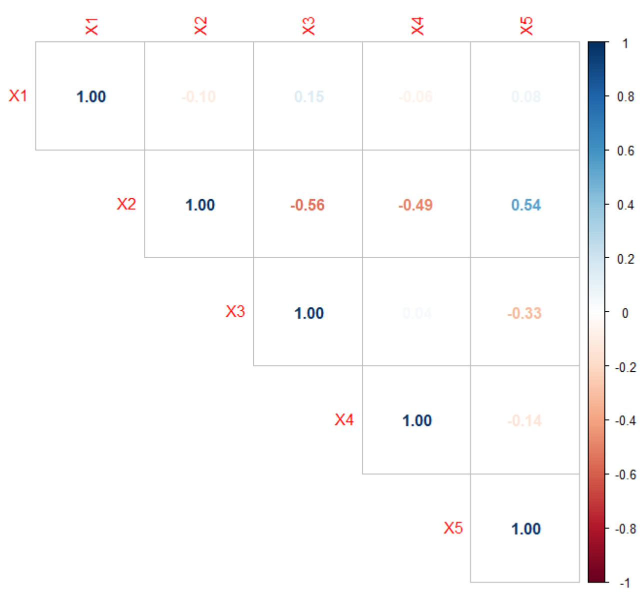

Figure 4. Correlation matrix year 2018

Source: Author's own research

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The table illustrates the generation of five principal components, corresponding to the number of initial variables for each year. Every component contributes to some portion of the overall variance in the dataset. The following explanation applies to the investigation conducted in 2018. The analysis for the other years is analogous. By examining the cumulative proportion, we can observe that the first component contributes to approximately 42% of the overall variation, while the first two components combined represent nearly 65%. Considering Kaiser's criterion in the analysis requires considering the first two principal components, as these are the sole components with a standard deviation exceeding 1.

Table 4.PCA summary

Year	2018		2019		2020		2021		2022	
Importance of components	Std. dev	Cum. Prop	Std. dev	Cum. Prop	Std. dev	Cum. Prop	Std. dev	Cum. Prop	Std. dev	Cum. Prop
Comp. 1	1.456	0.424	1.470	0.432	1.500	0.450	1.497	0.448	1.483	0.440
Comp. 2	1.059	0.648	1.043	0.650	1.047	0.669	1.049	0.668	1.059	0.664
Comp. 3	0.964	0.834	0.938	0.826	0.931	0.842	0.878	0.823	0.888	0.822
Comp. 4	0.778	0.955	0.803	0.955	0.756	0.957	0.803	0.951	0.782	0.944
Comp. 5	0.472	1.000	0.475	1.000	0.464	1.000	0.493	1.000	0.529	1.000

Source: Author's own research.

The factor matrix illustrates relationships between X variables and Z principal components, providing a meaningful explanation for the newly generated components. During the initial 3-year period, it is evident that the principal component demonstrates a significant negative connection with variables employment rate and employment in technology and knowledge-intensive sectors, while showing a positive association with average number of usual weekly hours of work in main job. The second principal component has a robust positive association with population and an almost negative correlation with long-term unemployment. The first principal component aggregates data regarding the rate of employment and the average number of usual weekly hours of work, whereas the following component considers the adverse aspects of the economy in relation to the population and prolonged unemployment. Over the past 2 years of examination, there have been modifications in the creation of the factor matrix. During this period, the principal component revealed a moderate negative correlation with variables average number of usual weekly hours of work in main job and long-term unemployment, and a positive correlation with employment rate and employment in technology and knowledge-intensive sectors. The second principal component had a substantial positive correlation with variable population and a statistically negligible negative correlation with any indicator. The first principal component is associated with employment rate, while the second principal component is related to dimension or size. It should be noted that for the years 2021 and 2022, the principal component values for all variables should be treated as having the opposite sign to their original sign, meaning they should be multiplied by -1.

Table 5. Factor matrix

Year	Variables	Comp. 1	Comp. 2	Comp. 3	Comp. 4	Comp. 5
2018	X1	0.101	0.818	0.488	0.285	0.044
	X2	-0.926	0.023	-0.112	0.033	0.359
	X3	0.697	0.413	-0.266	-0.491	0.180
	X4	0.515	-0.516	0.652	-0.060	0.196
	X5	-0.709	0.117	0.428	-0.528	-0.144
2019	X1	0.113	0.882	0.350	0.292	0.043
	X2	-0.927	-0.010	-0.071	0.032	0.367
	X3	0.708	0.339	-0.295	-0.510	0.190
	X4	0.557	-0.405	0.701	-0.034	0.181
	X5	-0.691	0.179	0.415	-0.545	-0.144
2020	X1	0.079	0.893	0.377	0.226	0.062
	X2	-0.927	-0.058	-0.077	0.026	0.362
	X3	0.730	0.313	-0.341	-0.467	0.184
	X4	0.543	-0.410	0.708	-0.100	0.160
	X5	-0.745	0.176	0.318	-0.540	-0.146
2021	X1	0.096	0.911	0.286	0.273	0.069
	X2	0.900	-0.131	-0.167	0.060	0.376
	X3	-0.634	0.103	-0.653	0.396	0.057
	X4	-0.782	0.232	-0.023	-0.522	0.249
	X5	0.640	0.434	-0.484	-0.370	-0.178
2022	X1	0.071	0.884	0.407	0.206	0.078
	X2	0.886	-0.077	-0.205	0.081	0.401
	X3	-0.663	0.145	-0.535	0.501	0.050
	X4	-0.765	0.265	-0.158	-0.509	0.246
	X5	0.620	0.492	-0.520	-0.232	-0.224

Source: Author's own research.

Cluster analysis

The silhouette plot reveals that the ideal grouping approach varies annually. The table below provides a summary of the average silhouette information and the corresponding method utilised for each year. The ward hierarchical clustering technique was used for the years 2018 and 2020. For the remaining years, the k-means method is used, a partitioning clustering technique.

Table 6. Average silhouette and method

Values/Year	2018	2019	2020	2021	2022
Average silhhouette	0.39	0.41	0.42	0.37	0.34
Method	Ward	K-means	Ward	K-means	K-means

Source: Author's own research.

The cluster graph displayed refers to the year 2018 and includes an overall total of 329 regions. The first cluster coloured red comprises regions from the following countries: Romania, Germany, England, the Netherlands, the Czech Republic, Switzerland, Sweden, Finland, Portugal, and Denmark. The second green-yellow cluster encompasses regions from nations such as Romania, France, Croatia, Spain, Belgium, Bulgaria, and Slovakia. The third cluster in the shade of green encompasses regions from France, Bulgaria, Serbia, Greece, North Macedonia, and Italy. The blue cluster, consisting of Romania, France, Poland, Spain, Germany, England, and Italy, is the fourth cluster. The last purple cluster includes regions from Romania, Italy, Spain, Greece, and Turkey. The first cluster exhibits exceedingly high values for component 1, whereas the fifth cluster displays very high values for component 2.

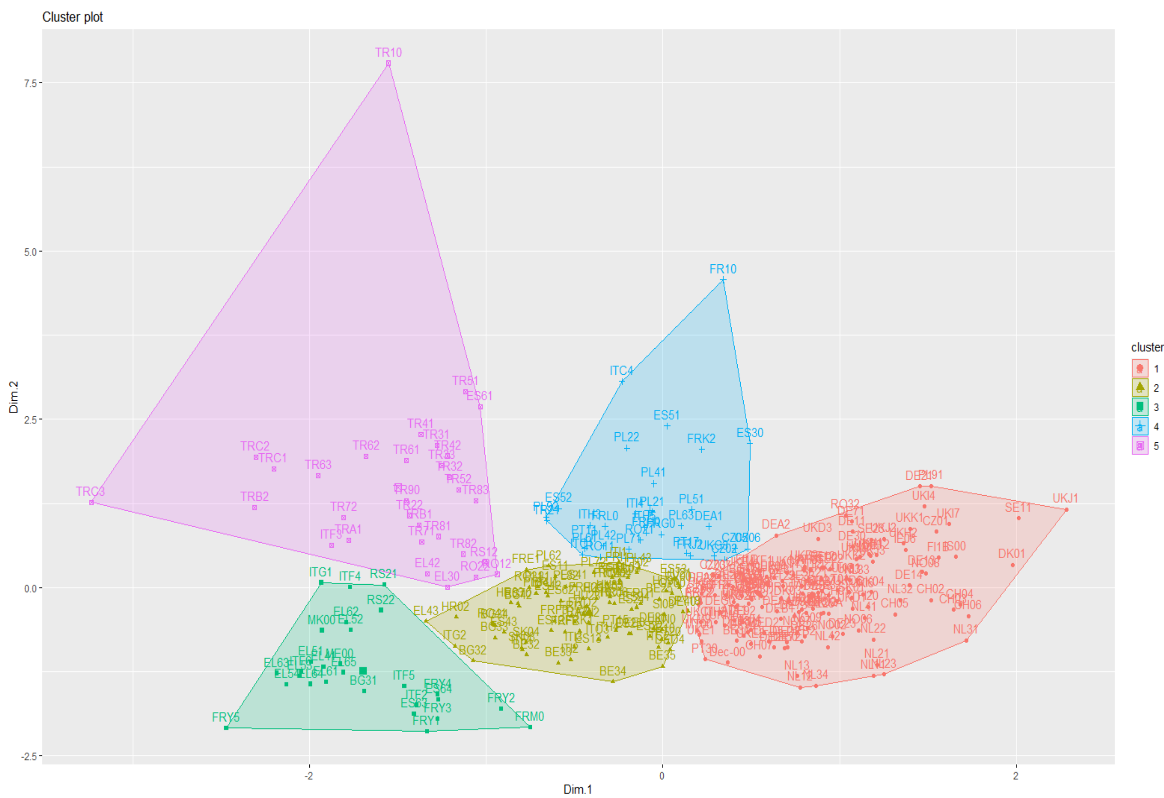

Figure 5. Cluster plot year 2018

Source: Author's own research.

For 2019, the first red cluster contains regions from: Romania, Spain, Poland, Italy, France, Portugal, Bulgaria, Belgium, Hungary, and England. Cluster two has 31 regions from countries like Serbia, Greece, Italy, France, and Bulgaria. The third cluster is the most comprehensive for this year and includes areas from France, Switzerland, Sweden, Germany, the Netherlands, Denmark, England, and the Czech Republic. The fourth cluster has seven regions, including one region in Turkey and one region each in Spain, France, and Italy. The last cluster contains only regions from Turkey, Greece, and Italy. The blue cluster reveals high values for component 2, while the green cluster displays great values for component 1.

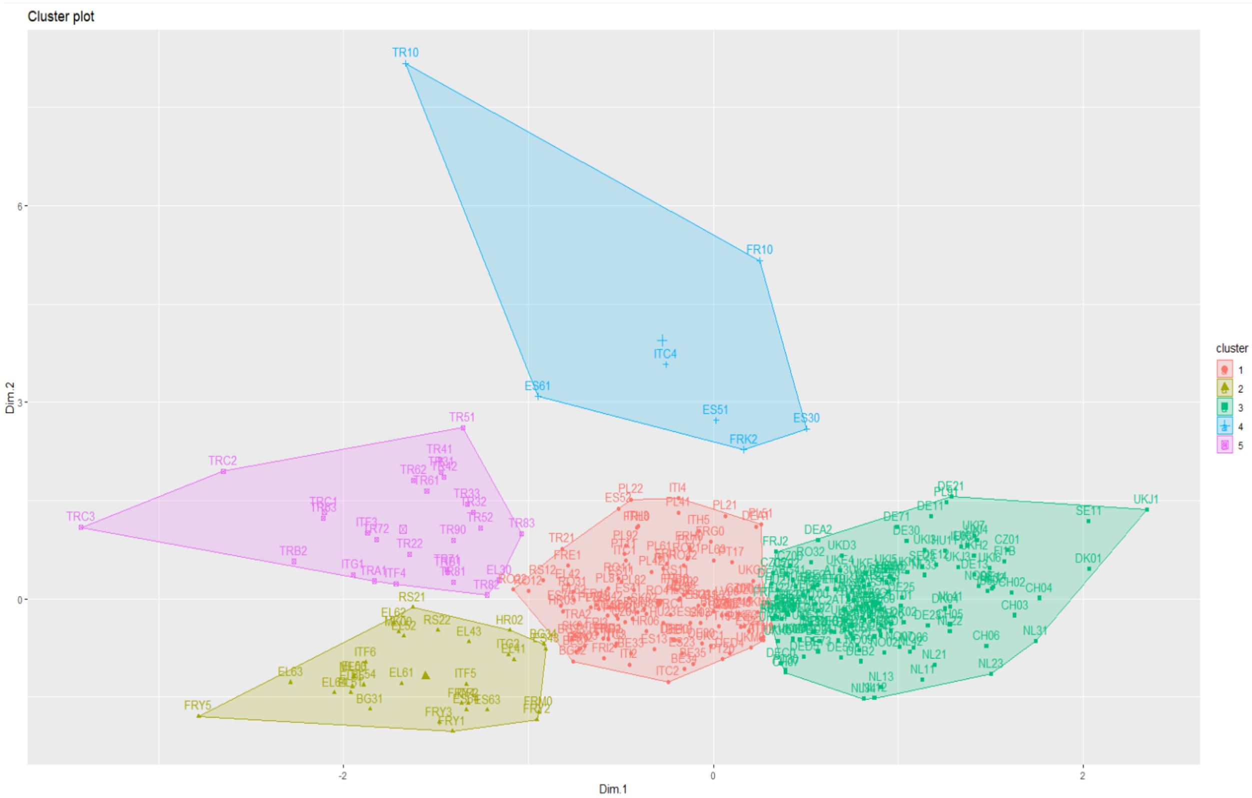

Figure 6. Cluster plot year 2019

Source: Author's own research.

The first cluster from 2020 covers the largest number of regions, specifically 125 from the following countries: Poland, Germany, Sweden, Denmark, Bulgaria, the Netherlands, Norway, Portugal, and Croatia. The second cluster is the second largest and contains territories from Romania, Poland, Greece, Italy, Spain, and Belgium. The green cluster incorporates lands from countries including Bulgaria, France, Italy, and Poland. The fourth blue cluster presents the highest number of areas from Turkey, followed by Greece, Serbia, and North Macedonia. The last cluster consists of one area from Turkey, one region from Italy, and later from France and Spain. The red cluster has elevated values for component 1, whereas the purple cluster demonstrates high values for component 2.

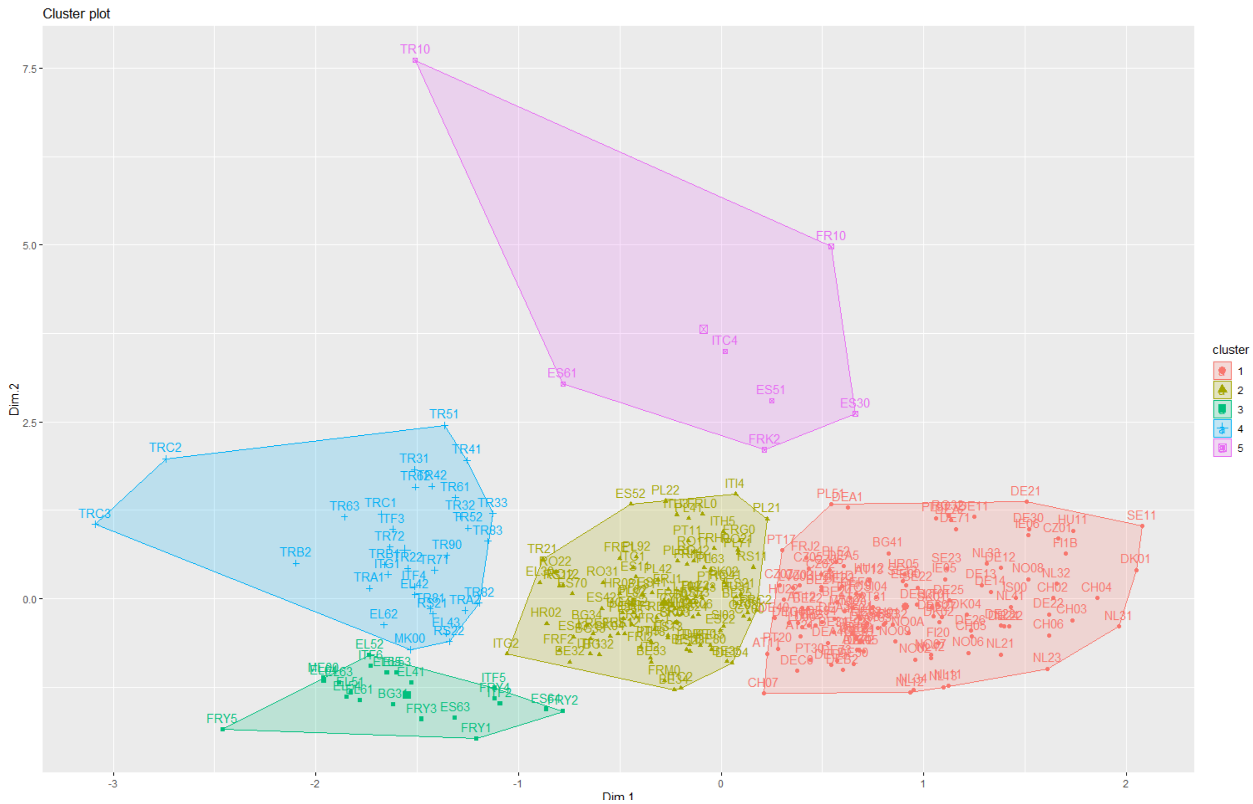

Figure 7. Cluster plot year 2020

Source: Author's own research.

The biggest cluster from 2021, characterised by its red colour, consists of provinces from multiple countries, including Romania, Italy, Spain, Poland, Bulgaria, France, Portugal, the Czech Republic, Hungary, Belgium, and Serbia. Similarly, the second cluster includes regions not only from Romania but also from Bulgaria, Germany, Switzerland, Lithuania, Norway, Hungary, Slovakia, Poland, and Finland. The third cluster is the smallest in terms of size. It contains one region from France, a couple of regions from Italy, and numerous counties from Spain. The blue cluster is the meeting point for regions from Belgium, Denmark, Serbia, Austria, Switzerland, the Netherlands, Norway, and Hungary. The regions of Romania, Greece, France, Bulgaria, Slovakia, and Spain converge in the purple cluster. The purple cluster exhibits low values for both components, whereas the green cluster demonstrates high values for both components.

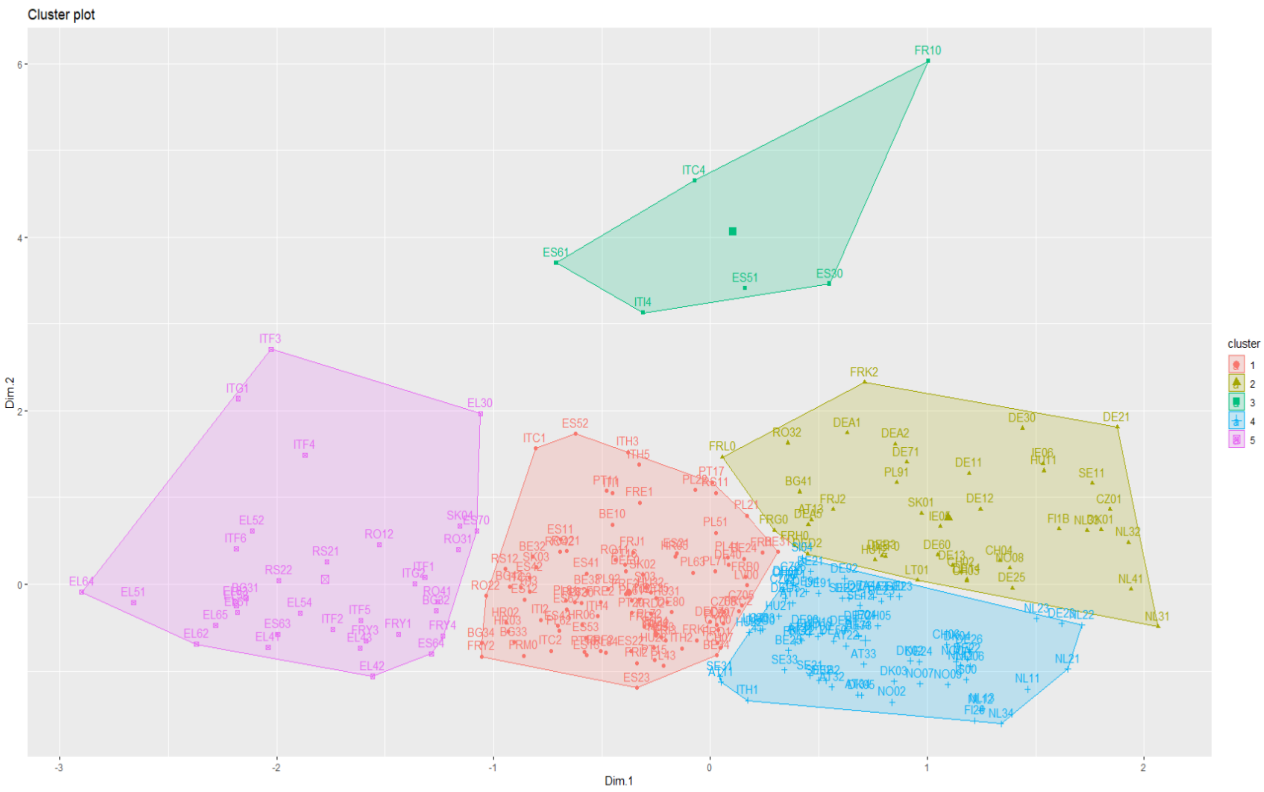

Figure 8. Cluster plot year 2021

Source: Author's own research.

Croatia, Austria, Sweden, Portugal, Finland, the Czech Republic, Switzerland, Lithuania, and Latvia are constituent regions of the red cluster. The second cluster covers regions from the Czech Republic, Switzerland, Germany, Serbia, Austria, Finland, Norway, Denmark, and Iceland. The third cluster, identified by the colour green, contains areas from Romania, Switzerland, Italy, Slovakia, France, and Serbia. In addition to Spain, Italy, France, Poland, and Hungary, the blue cluster also includes lands from Romania. The final cluster from 2022 spans regions not only from Romania but also from Poland, Slovakia, Portugal, Switzerland, Spain, and Italy. The green cluster indicates low values for both components.

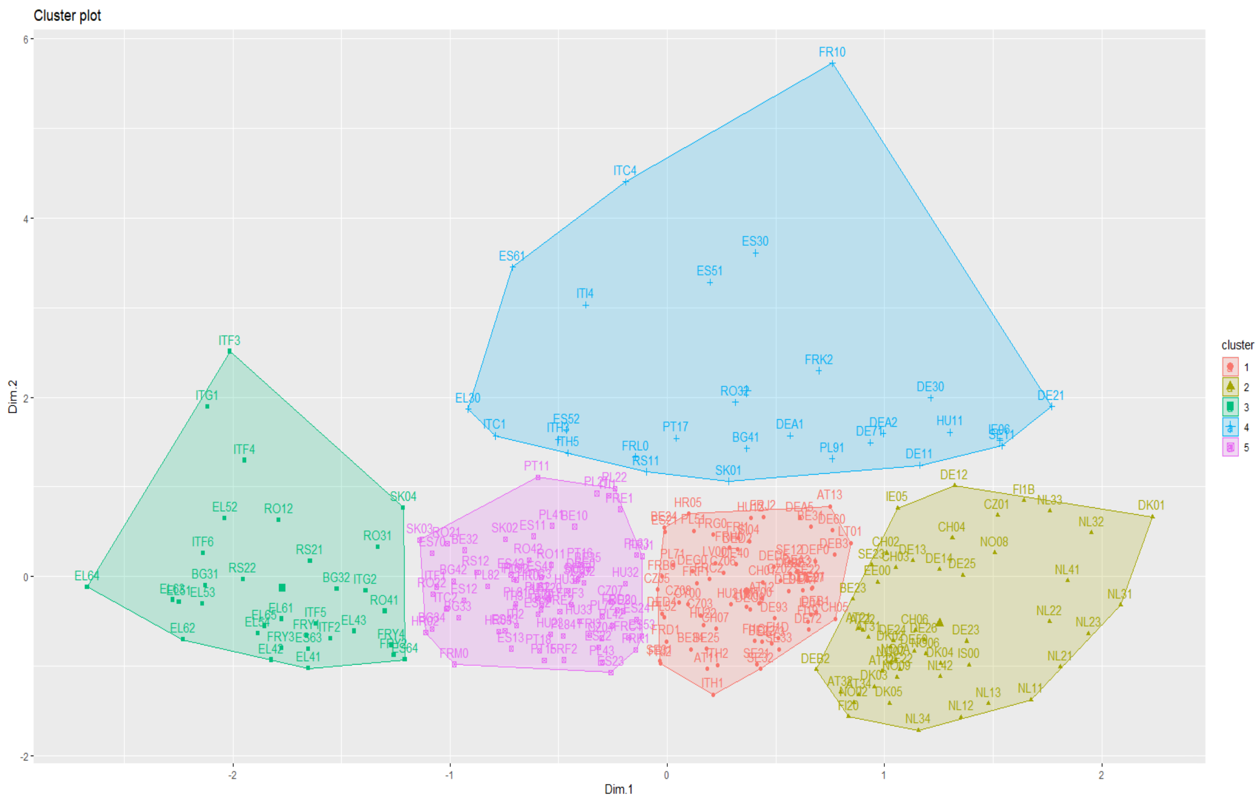

Figure 9. Cluster plot year 2022

Source: Author's own research.

There is a noticeable resemblance between the clusters in the years 2019 and 2020, and to some extent, a similarity can be detected with the year 2018. Concerning the clusters observed in 2021 and 2022, it can be stated that while there are some parallels between the two, there are significant disparities when compared to clusters observed in earlier years. The cluster analysis revealed that identical regions can be part of many clusters at different points during the analysed timeframe. Analysis of the cluster grouping performance shows positive values for both dimensions in the second blue cluster in 2018 and the second yellow-green cluster in 2021. At the same time, after the year 2021, a tendency for the graphs to present positive values for the second dimension can be observed.

The impact of the pandemic on the labour market varied depending on the pre-existing conditions of each country. Following the onset of the COVID-19 pandemic, countries with small sizes and low levels of employment experienced a decline in their economic performance, with their values gradually decreasing. On the contrary, the countries that had strong employment rates before to the pandemic, as a result of implementing measures in response to this occurrence, have exhibited even more impressive economic performance and growth.

Conclusion

The aim of this study was to examine the scientific literature concerning the effect of COVID-19 on the labour market in European regions, determine this impact, and identify the most affected indicators and/or regions. The results demonstrated that this phenomenon produced an impact on the labour market indicators and, correspondingly, on the regions of Europe in different manners. These findings arose from exploratory data analysis, performing principal component analysis, and conducting cluster analysis. Different patterns were evident prior to and following the onset of COVID-19. Although this study employs unique methods and techniques that are not commonly used, its goal is to evaluate the extensive and long-lasting effects of this event. Yet, the study does have certain limitations, such as its lack of detailed analysis on specific countries or categories of countries, its use of multiple indicators or alternative indicators, and its focus on certain periods in time. The COVID-19 pandemic has significantly impacted the labour market, requiring policymakers to develop targeted interventions, analyse employment patterns, and anticipate future challenges.

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Appendix

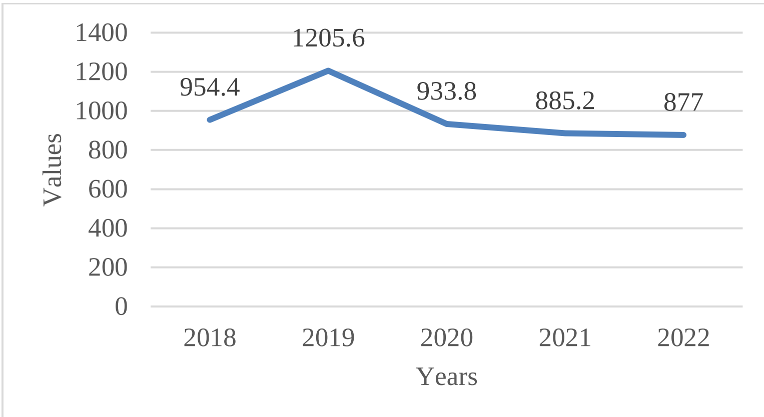

Figure 10. The evolution of the population over time

Source: Author's own research.

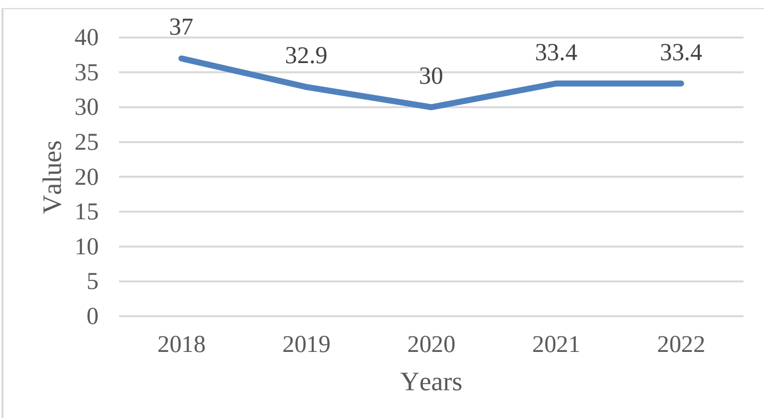

Figure 11. The evolution over time of long-term unemployment

Source: Author's own research.

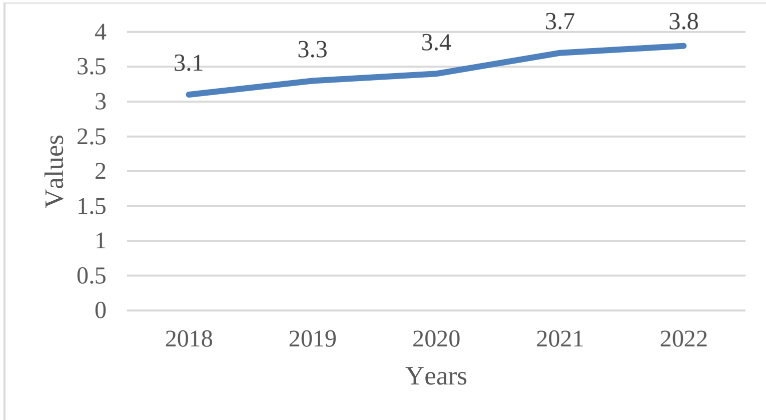

Figure 12. The evolution over time of employment in technology and knowledge-intensive sectors

Source: Author's own research.

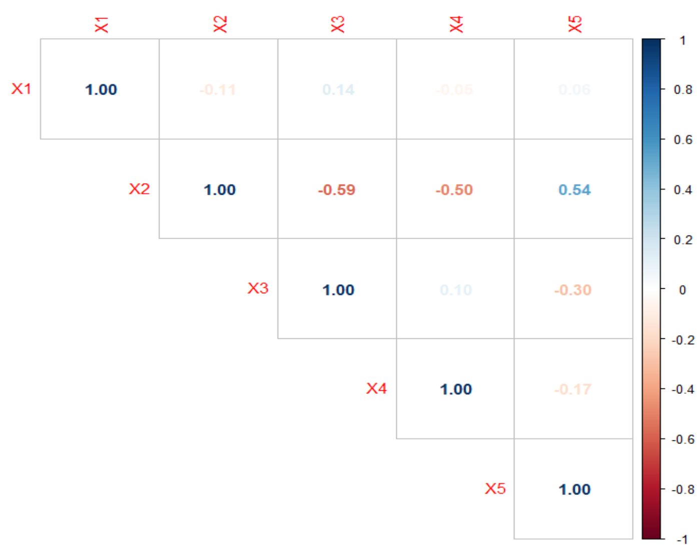

Figure 13. Correlation matrix year 2019

Source: Author's own research.

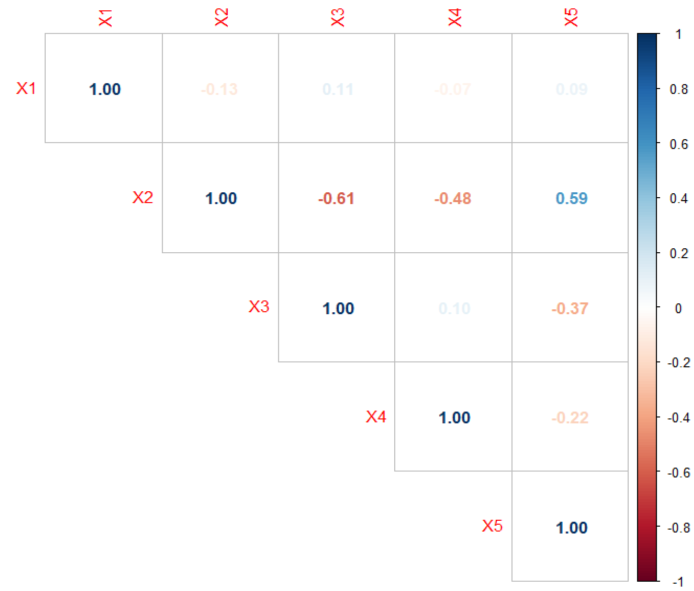

Figure 14. Correlation matrix year 2020

Source: Author's own research.

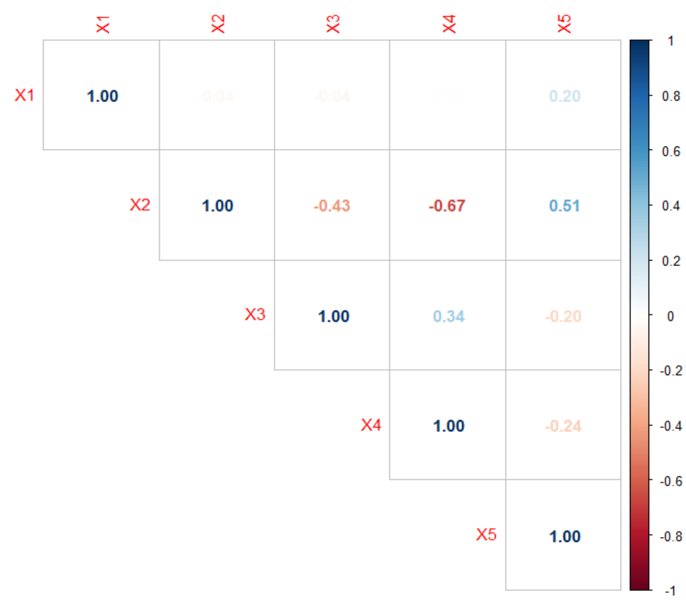

Figure 15. Correlation matrix year 2021

Source: Author's own research.

Figure 16. Correlation matrix year 2022

Source: Author's own research.