ECONOMICS
& Sociology

Stehlíková, B., Vincúrová, Z., Brezina, I., & Švihlíková, I. (2023). COVID 19 mortality as a reflection of the quality of health in EU countries. *Economics and Sociology*, *16*(3), 138-162. doi:10.14254/2071-789X.2023/16-3/8

COVID 19 MORTALITY AS A REFLECTION OF THE QUALITY OF HEALTH IN EU COUNTRIES

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Received: November, 2022
1st Revision: August, 2023
Accepted: September, 2023

DOI: 10.14254/2071-789X.2023/16-3/8

JEL Classification: I1, I14, I18, J10

ABSTRACT. The article aims to model the COVID-19 mortality in EU member states. It depends on chosen factors, determine the ranking of factors' importance and attempts for their reduction. Further objectives include identifying states with similar values of identified factors and their geographical concentration. This is exploratory research and is a quantitative research study according to the type of data used. Using the supervised machine learning random forest algorithm, we predict the number of COVID-19 deaths depending on analyzed factors. From 23 factors, we choose the seven most important factors. This selection is based on the highest value, Inc Node Purity. The cluster analysis is used to create groups of states with similar values of chosen factors. Because of the nonuniform methodology of reported deaths, we use excess mortality to measure COVID-19 mortality. The most important factor influencing COVID-19 mortality is the death rate due to circulatory system diseases. The second most significant factor is the avoidable mortality. The third most relevant factor is GDP per capita in purchasing power parity. Similar values of analyzed factors can be found in Bulgaria, Romania, the Czech Republic, Poland, Slovakia, Lithuania, Hungary, Croatia, and Latvia. COVID-19 mortality in these countries is almost three times higher than in the rest of the EU. Decision-makers could use the gained findings to decrease inequalities in the field of healthcare, mostly through efficient interventions in public healthcare and primary prevention. The results demonstrate that more investment in promoting health in the future will be necessary in the cohesion policy framework.

Keywords: COVID-19 mortality, excess mortality, EU, random forest regression, cluster analysis

Introduction

Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) appeared in December 2019 in Wuchan. The World Health Organization declared coronavirus disease (COVID-19) on March 11, 2020, as a global pandemic. A pandemic has significant consequences in all areas of economic life. The virus has strained healthcare systems around the world. In addition to healthcare, the pandemic significantly affected trade, finance, and consumption developments. Especially such sectors as tourism (Bilan et al., 2023; Vašaničová et al., 2023; Żemła & Szromek, 2023), hospitality, events sectors (Iwu et al., 2023), and the global airline industry were negatively influenced by the pandemic because of the travel bans (Zain et al., 2022). For instance, international tourist arrivals decreased by 75% in 2020 (Beha, 2023). It also hit the people hard in their daily lives. People are afraid of the consequences for their health and their work. Although businesses became more likely to go bankrupt during the pandemic (Civelek et al., 2023), some firms have flexible structures, such as small and medium-sized enterprises (Civelek et al., 2021) and have innovative attitudes (Kliuchnikava, 2022; Siderska et al., 2023) improved their adoption to new technologies (Dias et al., 2023) and remain resilient during crises (Kudej et al., 2021).

COVID-19 deaths are affected by several factors (Figure 1). The results of scientific works suggest that the pandemic caused by COVID-19 and similar future epidemics cannot be countered by medical studies alone. In this regard, there is a need to have an international and interdisciplinary study that examines the factors affecting Covid-19 mortality. Although some researchers analyse the financial impact of the pandemic in some European countries (Kolková & Ključnikov, 2021), investigate internationalization problems (Civelek & Krajčík, 2022) and financial issues of business in European countries (Ključnikov et al., 2022a) and compare European countries' enterprises from different perspectives (Ključnikov et al., 2022b), this paper not only focuses on socio-economic and environmental factors but also examines other factors from a widened perspective to shed lights on the reasons of Covid-19 mortality in various countries.

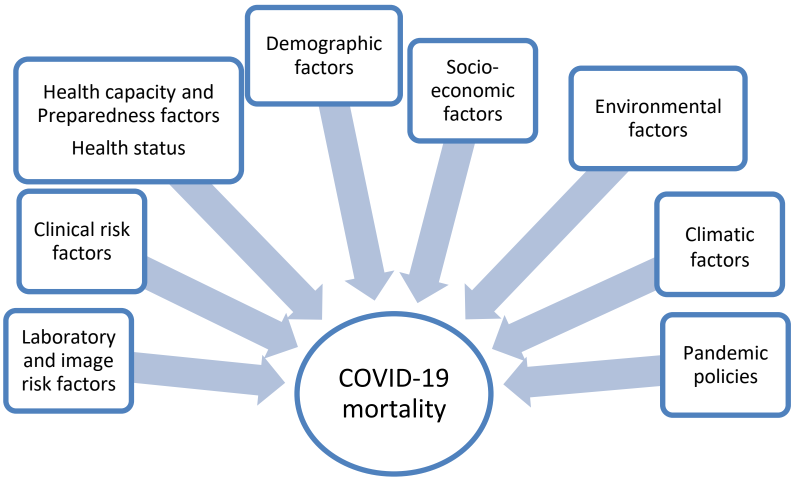

Figure 1. Factors affecting COVID-19 mortality
Source: *own processing*

1. Theoretical background

COVID-19 mortality

The impact of the COVID-19 pandemic was measured in various metrics. Information about the number of deaths from COVID-19 in the past days appeared most often in the news. For international comparison, it is necessary to recalculate the number of deaths per 100,000 inhabitants. In the case of the number of deaths from COVID-19, the situation is more complex. It should be emphasized that countries have different standards for reporting COVID-19 deaths. According to the WHO Guidelines, a death is recorded as a COVID-19 death if it is a probable or confirmed case of COVID-19 and there is no clear alternative cause of death that cannot be related to the disease of COVID-19. Definitions of death from COVID-19 in individual countries can be divided into two groups: based on clinical diagnosis (Belgium, Bulgaria, Croatia, Estonia, France, Germany, Ireland, Latvia, Lithuania, Malta, Poland, Portugal) or based on tests (Austria, Hungary, Italy, Netherland, Slovenia, Spain, Sweden) or hybrid (Greece, Cyprus, Romania) (WHO, 2020). This leads to the incomparability of mortality rates for COVID-19 between states. Due to the inconsistency of the reported deaths methodology, even the proportion of deaths to the total number of infected (used in epidemiology) is not a suitable indicator. The number of reported infected persons also depended on the intensity of testing in individual countries. Several authors have pointed out problems with the mortality data for COVID-19, for example, Sornette et al (2020). The impact of COVID-19 on the number of deaths was greater than on the number of YLL, as deaths from COVID-19 occur mostly in advanced age in Europe (Vieira et al., 2021). For this reason, even YLL is not a suitable indicator. It turns out that the objective indicator is excess mortality, that is, an increase in mortality from all causes compared to the expected mortality. Excess mortality is one of the most reliable approaches to measuring the impact of the COVID-19 pandemic Nepomuceno et al. (2022). Several authors, Karlinsky and Kobak (2021), and Wang et al. (2022), addressed mortality as a metric or its modeling.

Many studies have evaluated risk factors associated with mortality from COVID-19. We can divide them into several groups.

Laboratory and image risk factors

For example, the overview of the abnormal hematological and biochemical markers in individual COVID-19 patients is given by Aly et al. (2020) and Gallo Marin et al. (2021). This is a purely medical issue; the follow-ups are at the patient level. Therefore, we will not deal with it further.

Clinical risk factors

The second group consists of clinical risk factors. These physiological attributes may be associated with an increased risk of death at certain levels. (ScotPHO, 2021). The most frequently mentioned clinical risk factors are age, obesity, sex, and associated comorbidities Gallo Marin et al. (2021). The higher mortality rate in men may be due to gender-related immunological differences and/or an association with comorbidities (Editorial The Lancet (2020)). Older patient age increases the risk of death from COVID-19 (Zhou et al. (2020), Sasson (2021), Rahman et al., 2021), Davies (2021)). The authors of Borobia et al. (2021) also confirm the influence of the mentioned clinical factors - old age, men, comorbidities, and abnormal laboratory values were the most common factors behind the mortality of patients with COVID-19. According to Eurostat, obese people are people for whom the proportion of the weight (in kilos) and the square of the height (meter) equals or exceeds 30. The connection between obesity and death from COVID-19 was studied, for example, by Zhang et al (2020). The most common diseases associated with death from COVID-19 are cardiovascular diseases, diabetes mellitus, kidney disease, liver disease, cerebrovascular diseases, chronic obstructive pulmonary disease, chronic heart disease malignancies and acute pancreatitis (Aly et al., 2020, Sasson, 2021, Davies, 2021).

Health capacity, preparedness factors, health status

The immediate availability of hospital beds is an important indicator for assessing the capacity to provide care to patients. The results of studies on the connection between the availability of hospital beds and deaths from COVID-19 are not clear-cut. The differences result from the different evaluated periods of the pandemic, different types of beds (global hospital bed, acute care bed, intensive care unit bed), and different territories. A significant relationship between the number of intensive care unit beds per 100,000 inhabitants and mortality from COVID-19 was found by Sen-Crowe et al. (2021), Cobre et al. (2020), Mattiuzzi, Lippi and Henry (2021). Sen-Crowe et al. (2021), Souris and Gonzalez (2020), and Mattiuzzi, Lippi and Henry (2021) found that there is no significant dependence between the number of global hospital beds and acute care beds per 100,000 population and COVID-19 mortality. On the contrary, according to Sussman (2020), increasing the number of hospital beds has a significant impact on reducing mortality from COVID19. McCabe et al also dealt with the estimation of the necessary capacity of beds following the epidemiological simulation. (2021), Goic et al (2021), Weissman et al (2020). According to Mattiuzzi, Lippi and Henry (2021), Chaudhry et al (2020), the number of physicians and nurses has an indirect statistically significant effect on mortality from COVID-19. Different results were reached by Goh et al (2020). Kim et al (2022) - in their study confirmed only an indirect significant dependence of the number of deaths on COVID-19 and the number of physicians. Liang et al (2020), Di Bari et al (2020) confirmed the relationship between mortality from COVID and the number of tests.

Avoidable mortality (preventable and treatable) is mortality that can be prevented or to heal. It is defined as the causes of death in people under the age of 75, which can be avoided mainly by effective interventions in the field of public health and primary prevention (Eurostat, 2019). Avoidable Mortality is an indicator of the effectiveness of health services (Nante et al, 2021) We will use Avoidable Mortality as a metric of effectiveness of health services). Health status is a multidimensional phenomenon. The subject's self-assessment of his health status is a frequently used summary indicator of health status, because its correlation with other measures of health status is high and significant (Idler and Angel, 1990). The Survey on Income and Living Conditions (SILC) also uses a single question to measure health status. Preparedness can be assessed using the Global Health Security Index, which is the first internationally accepted comprehensive assessment and benchmarking of health security and related capabilities (GHS Index, 2019). Haider et al (2020) did not find an association between the GHS Index value and mortality from COVID-19. Results Kumru, Yiğit and Hayran (2022) reached the opposite conclusion in their study. Khan et al (2020) found that health care expenditures, while not reaching statistical significance, were associated with COVID mortality.

Demographic factors

Analyses by several authors (Bhadra, Mukherjee and Sarkar (2021), Kadi and Khelfaoui (2020), Kuzmenko et al. (2020), Khan et al (2020)) confirm a positive correlation between density population and by COVID-19 infection and related mortality. Although high density may support the spread of disease and increase mortality from COVID-19, differences in preventive measures and socio-economic factors may disrupt this dependence (Wong and Li (2020), Carozzi (2020). Kozlovskyi et al 2020). The results of Kapitsinis et al. (2020) did not confirm the dependence of mortality on COVID-19 and population density. Distance, relative isolation, and lower population density mean that in rural areas the contagion spreads more slowly and thus one would expect a lower death rate. In rural areas, however, lower performance of the health system can be assumed due to the lack of qualified health workers as well as greater distance from large hospitals and the resulting poorer access to specialized services (WHO European Region, 2010). It should also be borne in mind that rural residents tend to be older than urban residents. Rural residents are also more at risk of poverty or social exclusion than urban residents. Rural residents mostly have jobs that are less well paid and for which home office could not be applied. Therefore, it is not surprising that the conclusions regarding the mortality of the rural population are not clear-cut. COVID-19 mortality rates have been higher in rural counties (Monnat (2021), Huang et al (2021), Peters (2020), Grome (2022), Meo et al (2020)). In the first wave of the pandemic, rural regions in EU countries recorded a lower excess mortality from COVID-19 than urban regions. Differences during the second wave are less clear. (Natale et al (2021). Populations with a higher degree of urbanization in OECD countries have a greater number of deaths from COVID-19 (Davies, 2021). In eastern England more urban areas saw excess cases reported by Brainard et al.(2020).We have already analysed some of the demographic factors in the clinical risk factors section.

Socio-economic factors and other

Research shows that socio-economic inequalities also have an impact on the number of deaths from COVID-19. According to Miller, Wherry and Mazumder (2021), installation, maintenance, repair and manufacturing workers experienced the highest mortality rate from COVID-19. Goutte, Péran and Porcher (2020), Sun, Hu and Xie (2021) found that higher unemployment and poverty rates increase the mortality rate from COVID-19. According to Paul et al (2021), higher unemployment rates were significantly associated with higher mortality rates (only in urban districts). It can be caused by the higher share of “frontline workers” in urban communities and the higher risks in their employment consequently (Mishchuk et al., 2023; Remeikienė & Bagdonas, 2021).While the percentage of college-educated residents reduced mortality from COVID-19 in both urban and rural counties. The results of Wildman (2021), Deaton (2021) speak of a strong dependence between income inequality and the number of deaths from COVID-19. Greater differences in income lead to higher mortality. The use of real GDP per capita as a measure of economic development is widely represented in the literature. The better economic situation of the country and higher spending on healthcare contribute positively to the decrease in mortality, respectively. to maintain a lower death rate in general. Countries with lower GDP per capita are probably associated with greater deprivation of the population, which means worse health conditions, limited access to health services. Higher GDP correlates with lower mortality from COVID-19 (Phannajit et al (2021), Lippi et al (2020)).

Environmental factors

Studies have shown that several air pollutants cause an increase in mortality from COVID-19. High concentrations of pollutants in the atmosphere and their long-term exposure increase mortality from COVID-19, this increase was confirmed by Ogen (2020). Yu et al (2021), Osuna, Castañeda, and Rebolledo (2022), Mele and Magazzino (2021), Frontera et al 2020.

Climatic factors

Excess winter mortality has been attributed in epidemiology to physiological responses to cold exposure and air pollution (Telfar-Barnard et al (2020)). Demongeot et al (2020) showed that the virulence of coronavirus diseases decreases in humid and hot weather. Low temperature and humidity increase mortality from COVID-19. (Ma et al, 2020, Rahman et al, 2021, Anis, A. (2020), Sajadi et al (2020 Malki, et al (2020), Demongeot, Flet-Berliac and Seligmann (2020), Yao et al (2020), Zilberlicht et al (2021)).Mao et al (2020) found that in countries with high temperatures and low humidity, the incidence of deaths from COVID-19 is lower than in countries with low temperatures and high humidity Latitude analysis in relation to deaths from COVID-19 was addressed by Sajadi et al (2020). According to the results of Burr et al (2021) temperature and latitude s correlate with mortality from COVID-19. We can describe the temperature zones using cooling degree day (describe the need for the air-conditioning requirements) and heating degree day (need for the heating energy requirements).

Pandemic policies

In the early days of the spread of the new coronavirus, it was possible to observe in some states a relative unpreparedness and indecision to take the necessary measures and implement them in the fight against the pandemic. The gradual spread of COVID-19 triggered a series of measures by the governments of individual countries. There was the closing of schools, the transition to home offices, restrictions on mobility, bans on public gatherings, investments in medical facilities, or their reprofiling, contact tracing and other interventions. Quantification of the range of measures to restrict movement is given by van der Wielen and Barrios (2021). According to Jinjarak et al (2020), the application of stricter pandemic policies was associated with significantly lower mortality growth rates during the first wave. The Oxford COVID-19 Government Response Tracker (OxCGRT) provides a systematic set of government responses. The Oxford Stringency Index (OSI) is a tool developed by the University of Oxford to quantify the stringency of government policies. A higher score indicates a stricter response. Sorci, Faivre, and Morand (2020) explain differences between countries in mortality from COVID-19 using OSI. Fuller et al (2021) evaluated the impact of the timing of policies on mortality from COVID-19.

The contribution aims to model the mortality rate from COVID-19 in EU countries depending on the selected factors, determine the order of their importance, try to reduce them, and identify states with similar values of the analyzed factors and their geographical concentration. To fulfill the goal, we formulated three scientific hypotheses.

H1: Only selected indicators are needed to build a good model of COVID-19 mortality;

H2: COVID-19 mortality is higher in post-socialist states;

H3: The values of factors determining mortality from COVID-19 are worse in post-socialist EU countries than in the rest of the EU.

2. Data and methods approach

In the article, we will work with excess mortality estimates for 2020 according to Karlinsky and Kobak (2021) as an indicator of COVID-19 mortality.

Based on the literature study, we included the variables listed in Table 1 in the analysis. All data come from publicly available databases (Table1). We did not directly include environmental factors in our study. Diseases that cause respiratory diseases (pollutants O3, PM, NO2, SO2), cardiovascular disease (pollutants O3, PM, SO2) are included.

Table 1. Used indicators and data sources

Indicator	Year	Data source	Acronym
Population density (logarithm)	2019	Eurostat [HLTH_EHIS_BM1E]	LnDensity
Rural population (% of total population)	2019	[1]	Rural
Cooling degree days	2019	Eurostat [NRG_CHDD_A]	CDD
Heating degree days	2019	Eurostat [NRG_CHDD_A]	HDD
Proportion of population aged 65 and over	2019	Eurostat [TPS00028]	AgeMore65
Health care expenditure (all financing schemes) as percentage of GDP	2019	Eurostat [HLTH_SHA11_HF]	HExp
Avoidable mortality (per 100,000 inhabitants)	2019	Eurostat [HLTH_CD_APR]	AvoidableMort
Available beds in hospitals per 1,000 inhabitants	2019	Eurostat [HLTH_RS_BDS]	HBeds

[1] https://data.worldbank.org/indicator/SP.RUR.TOTL.ZS?end=2019&start=1960

Acute care hospital beds per 1,000 inhabitants	2019	[2]	AcutBeds
Practising nurses per 1,000 inhabitants	2018	[3]	Nurses
Physicians per 1,000 inhabitants	2018	[4]	Physicians
Global Health Security Index	2019	[5]	GHSI
Rate of death due to diseases of respiratory system	2018/**	Eurostat [hlth_cd_asdr2]	Mresp
Rate of death due to diseases of circulatory system	2018	Eurostat [hlth_cd_asdr2]	Mcircul
Rate of death due to diabetes mellitus	2018/**	Eurostat [TPS00137]	Mdiabetes
Percentage of obese inhabitants	2019	Eurostat [HLTH_EHIS_BM1E]	Obese
Percentage of persons reporting a chronic disease high blood pressure	2019	Eurostat [hlth_ehis_cd1e]	Blood
Percentage of persons reporting a chronic respiratory diseases (excluding asthma)	2019	Eurostat [hlth_ehis_cd1e]	Respir
Percentage of persons reporting a diabetes	2019	Eurostat [hlth_ehis_cd1e]	Diabetes
Percentage of inhabitants smoking of tobacco products	2019	Eurostat [HLTH_EHIS_SK1E]	Smoker
Percentage of inhabitants Self-perceived health as very good	2019	Eurostat [HLTH_SILC_02]	HVeryGood
Oxford Stringency Index (April 1 2020)	2020	[6]	OSI20
GDP per capita, purchasing power parity (logarithm)	2019	Eurostat [NAMA_10R_2GDP]	LnGDP
Excess mortality (by Karlinsky, Kobak, 2021) as estimation of the Covid-19 mortality (per 100,000 inhabitants)	2020		Emort100

Notes: /* Bulgaria, Croatia, Cyprus, Malta, Romania last available 2013-2015 /** France 2017
Source: *own processing*

In the first step, we calculated descriptive characteristics for the analysed variables. In the second step, we used a standardized regression coefficient, the so-called beta coefficient. The higher the absolute value of the beta coefficient, the stronger the effect (Meyers, Gamst, and Guarino, 2016).

In the third step, we used random forest regression to identify influential variables. Random forest is a supervised learning algorithm that uses an ensemble learning method for regression (Guyon, Statnikov and Batu, 2019). A random forest combines the results of multiple predictions. IncNodePurity is the total decrease in node impurities from splitting on the variable, averaged over all trees. For classification, the node impurity is measured by the Gini index. Inc Node Purity was used as a measure of variable importance.

We assessed the quality of the estimate using the following metrics (Watson and Teelucksingh, 2002). Mean absolute error (MAE) measures the average of the residuals in the dataset. Root Mean Squared Error (RMSE) measures the standard deviation of residuals. The Coefficient of determination (R-squared) tells how well the predictor variables can explain the variation of the dependent variable. Represents the proportion of the variance in the dependent variable which is explained by the model.

We identified groups of similar countries in terms of evaluated factors using cluster analysis. We verified the clusterability of the data set using the Hopkins statistic. (Frank and Todeschini, 1994). We chose the method for hierarchical clustering based on the maximum value of the agglomerative coefficient (Hair, 2009). We determined the number of clusters

[2] https://tradingeconomics.com/country-list/icu-beds?continent=europe
[3] https://stats.oecd.org/
[4] https://data.worldbank.org/indicator/SH.MED.PHYS.ZS
[5] https://www.ghsindex.org
[6] https://elifesciences.org/articles/69336

using the Tibshirani Gap statistic method (Tibshirani, Walther, Hastie, 2001; Kassambara, 2017). We used a tanglegram to visually compare the hierarchical clustering results.

We used the R computing environment (R Core Team, 2021).

3. Results and discussion

Excess mortality is one of the most reliable approaches to measure mortality from COVID-19 according to the available literature. In our paper, we use estimates (Emort100) published by Karlinsky and Kobak (2021). We included 23 indicators in the analysis, the selection of which is based on a literature review, and their descriptive statistics are shown in Table 2. The largest variability measured by the coefficient of variation is after CDD (143.91) the dependent variable just examined is excess mortality (71.72). The third largest variability is the rate of death due to diabetes mellitus (56.10). Rural population (% of total population) has a coefficient of variation of 50.11. Percentage of inhabitants Self-perceived health as very good has a coefficient of variation of 46.89.

Data distribution is for 13 indicators fairly symmetrical (skewness between -0.5 and 0.5). Others are moderately skewed (skewness is between -1 and – 0.5 or between 0.5 and 1). For positive values of skewness the right-hand tail will be longer than the left-hand tail. Skewness is positive for all indicators except for three indicators - Rural population, Proportion of population aged 65 and over and Oxford Stringency Index.

Table 2. Descriptive statistics

Indicator	**Min**	**Max**	**Mean**	**Sd**	**Median**	**coefficient of variation**	**skewness coefficient**
LnDensity	2.90	7.37	4.67	0.94	4.66	20.13	0.61
Rural	1.92	46.24	26.24	13.15	28.6	50.11	-0.15
CDD	0.00	756.22	140.48	202.17	59.42	143.91	2.5
HDD	515.23	5482.97	2638.52	1121.49	2600.72	42.50	0.47
AgeMore65	14.10	22.90	19.33	2.17	19.60	11.23	-0.80
Hexp	5.37	11.70	8.28	1.81	7.84	21.86	0.26
AvoidableMort	164.86	504.13	280.09	114.09	225.10	40.73	0.76
Hbeds	2.7	7.91	4.90	1.73	4.53	35.31	0.12
AcutBeds	1.90	5.95	3.73	1.10	3.41	29.49	0.45
Nurses	3.40	14.30	8.17	3.1	7.20	37.94	0.39
Physicians	2.40	6.10	3.83	0.80	3.70	20.89	0.87
GHSI	55.00	93.80	74.09	8.60	74.20	11.61	0.06
Mresp	3.20	13.00	7.77	2.95	7.40	37.97	0.23
Mcircul	22.60	65.80	38.41	11.34	36.20	3.35	0.64
Mdiabetes	0.99	5.85	2.46	1.38	2.00	56.10	1.16
Obese	10.90	28.70	18.42	4.20	17.70	22.80	0.47
Blood	11.60	37.30	22.89	6.26	21.80	27.35	0.30
Respir	0.60	6.40	3.60	1.56	3.40	43.33	0.12
Diabetes	3.50	12.10	7.9	1.86	7.00	23.54	0.51
Smoker	12.60	36.20	23.63	4.74	24.00	20.06	0.06
HVeryGood	4.70	46.80	22.51	10.55	21.10	46.89	0.85
OSI20	64.81	96.30	80.73	7.20	81.48	8.92	-0.09
LnGDP	9.71	11.27	10.27	0.35	10.19	3.41	0.95
Emort100	-10.00	460.00	163.70	117.41	140.00	71.72	0.61

Source: *own calculations*

Beta coefficient is the degree of change in the COVID-19 mortality for every 1-unit of change in the predictor variable. Table 3 contains beta coefficients for individual indicators sorted by the absolute value of the beta coefficient. Twelve of them are statistically significant. A positive sign of the beta coefficient means that the variable contributes to the increase of COVID-19 mortality. The second part of the table contains the results of Random Forest regression. It contains values of Inc Note Purity, which is used as a measure of variable importance. The first four most important indicators are identical to the indicators having the highest absolute value of the beta coefficient - Rate of death due to diseases of circulatory system, Avoidable mortality, GDP per capita purchasing power parity (logarithm). Others are Available beds in hospitals per 1,000 inhabitants, Acute care hospital beds per 1,000 inhabitants, Percentage of persons reporting a chronic disease high blood pressure, Global Health Security Index. For other indicators, node purity (Inc Node Purity) values are smaller.

The first five most important indicators are the same for both methods (the difference in order is one or zero). Spearman's correlation coefficient between ranks for both methods for all 23 indicators is high 0.855731 and significant (p value is <0.0001). Which confirms that the order of results obtained by both methods does not differ significantly.

Table 3. Beta coefficients for linear regression model and node purity for random forest regression

Method	**Linear r*egression* model**					**Random forest regression**	
Indicator	**Rank**	**Estimate**	**Std. Error**	**t - value**	**Pr(>|t|)**	**Rank**	**Inc Note Purity**
Mcircul	1	7.237e-01	1.380e-01	5.243	1.99e-05 ***	2	53129.375
AvoidableMort	2	6.833e-01	1.460e-01	4.679	8.56e-05 ***	1	54257.101
LnGDP	3	-6.436e-01	1.531e-01	-4.204	0.000293 ***	4	27146.849
Hbeds	4	5.973e-01	1.604e-01	3.724	0.00100 **	3	27072.591
AcutBeds	5	5.401e-01	1.683e-01	3.208	0.00364 **	5	21881.889
Nurses	6	-5.336e-01	1.692e-01	-3.154	0.00416 **	8	10988.051
Smoker	7	5.325e-01	1.693e-01	3.146	0.00424 **	14	8219.679
Blood	8	5.324e-01	1.693e-01	3.144	0.00426 **	6	19512.673
GHSI	9	-4.869e-01	1.747e-01	-2.787	0.0100 *	7	13693.894
Mresp	10	-4.583e-01	1.778e-01	-2.578	0.0162 *	10	9975.738
Rural	11	4.456e-01	1.790e-01	2.489	0.0198 *	9	10649.202
HVeryGood	12	-4.388e-01	1.797e-01	-2.441	0.0221 *	11	9459.197
Hexp	13	-3.789e-01	1.851e-01	-2.047	0.0513	12	9289.420
Diabetes	14	1.733e-01	1.970e-01	0.88	0.387	23	2457.451
AgeMore65	15	1.634e-01	1.973e-01	0.828	0.415	18	4503.694
Mdiabetes	16	-1.511e-01	1.977e-01	-0.764	0.452	22	3881.861
Obese	17	-1.489e-01	1.978e-01	-0.753	0.459	13	9271.079
CDD	18	1.442e-01	1.979e-01	-0.728	0.473	15	5744.977
LnDensity	19	-1.146e-01	1.987e-01	-0.577	0.569	21	3972.598
Physicians	20	-9.044e-02	1.992e-01	-0.454	0.654	20	4286.815
HDD	21	-6.366e-02	1.996e-01	-0.319	0.752	16	5560.081
Respir	22	2.418e-02	1.999e-01	0.121	0.905	17	4879.837
OSI20	23	1.196e-02	2.000e-01	0.06	0.953	19	4439.921

Note: * p < 0.05, ** p < 0.01, *** p < 0.001

Source: *own calculations*

The coefficient of determination for random forest regression for 23 predictors is high (0.9480). The predictor variables included in the random forest explain very well the deviations of the dependent variable. However, there are many variables included in the model (23). Our question is whether they are all really necessary. For the seven most important indicators identified using random forest regression, the average value of the residuals is only slightly larger than in the model with all variables. The residuals' standard deviation in the random forest case for the seven most important indicators is even slightly smaller. The decrease of the coefficient of determination to the value of 0.9358 by the value of 0.0122 is negligible. Therefore, we will use the first seven most important indicators in the model.

Table 4. Comparison of random forest regression models

Indicator	MAE	RMSE	R2
All 23 indicators	29.954	36.428	0.9480
AvoidableMort	39.382	47.435	0.8425
AvoidableMort, Mcircul	33.873	42.606	0.8886
AvoidableMort, Mcircul, LnGDP	34.916	42.965	0.8948
AvoidableMort, Mcircul, LnGDP, Hbeds	33.693	39.381	0.9192
AvoidableMort, Mcircul, LnGDP, Hbeds, AcutBeds	32.7556	38.765	0.9274
AvoidableMort, Mcircul, LnGDP, Hbeds, AcutBeds, Blood	31.320	36.636	0.9309
AvoidableMort, Mcircul, LnGDP, Hbeds, AcutBeds, Blood, GHSI	30.7302	35.290	0.9358
AvoidableMort, Mcircul, LnGDP, Hbeds, AcutBeds, Blood, GHSI, Nurses	30.682	36.192	0.9372

Source: *own calculations*

Although the addition of the eighth variable Nurses to the model slightly decreased the MAE, the RMSE increased, and the increase in the R2 value is also small. Therefore, we decided to work with seven variables. Figure 2 shows the node purity values for the seven most important indicators.

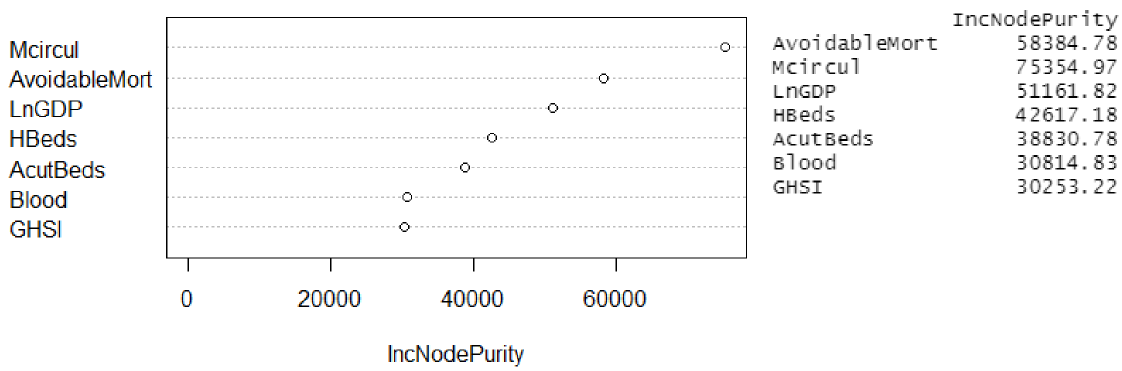

Figure 2. Random Forest variables importance to predict COVID-19 mortality for the seven most important indicators and its node purity
Source: *own calculations*

In Figure 3, we see that the estimates of COVID-19 mortality obtained using 23 variables and 7 variables are not very different. For some states they are almost identical. It would be ideal if the estimates were on the grey line (i.e. the estimate would be equal to reality). We can also see from the figure that the estimates are good except for extremely high values of COVID-19 mortality.

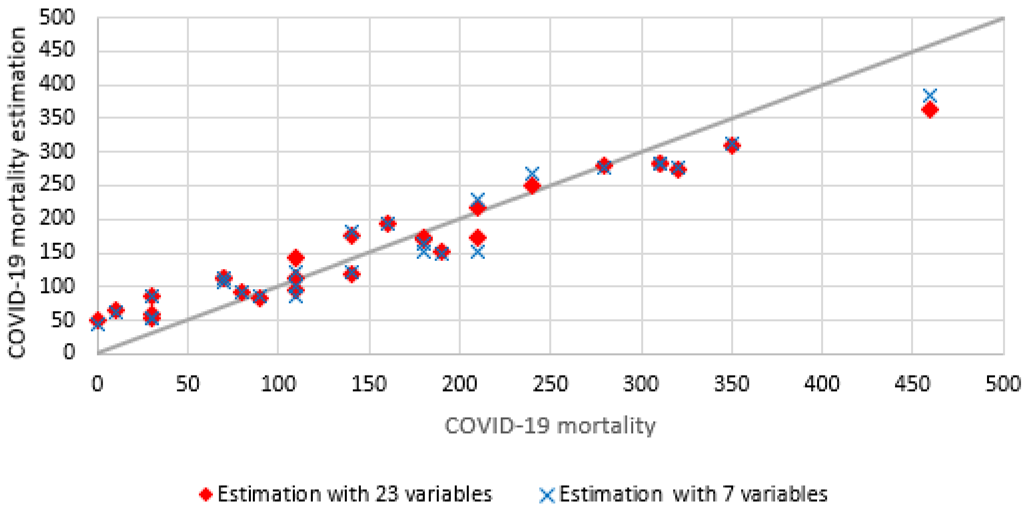

Figure 3. COVID-19 mortality estimation using random forest regression
Source: *own calculations*

In the next step, we proceed to create clusters based on similar values of the aggregated factors. We will work in parallel with two models – a model with 23 variables and a model with 7 most important variables.

The value of the Hopkins statistic H is 0.6035 for all indicators. When we use the seven most influential indicators, it is 0.630441. Both are above the threshold 0.5, i.e. a data set with 23 and 7 variables are clusterable. A little more for the seven most influential indicators. Ward's minimum variance method produces the highest agglomerative coefficient for all indicators and the 7 most influential ones (all indicators: average – 0.4578, single - 0.3426, complete - 0.6347, ward - 0.7454; seven most influential ones: average – 0.6319, single – 0.4366, complete - 0.7911, ward - 0.8734). Therefore, we use ward method for our final hierarchical clustering for both clustering. The optimal number of clusters is two in both cases.

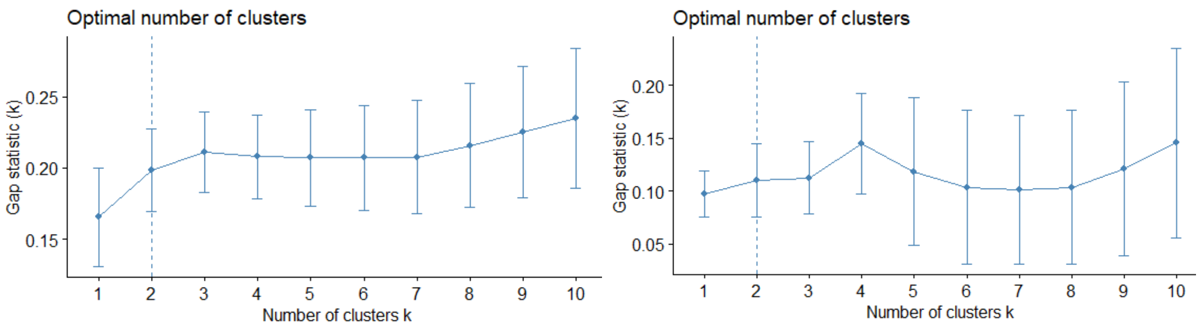

Figure 4. Determining the optimal number of clusters
Source: *own calculations*

The Mantel statistic value of 0.6687 is significant (p value is 0.001). This means that the distances in the matrix with 23 variables are significantly correlated with the distances with 7 predictors.

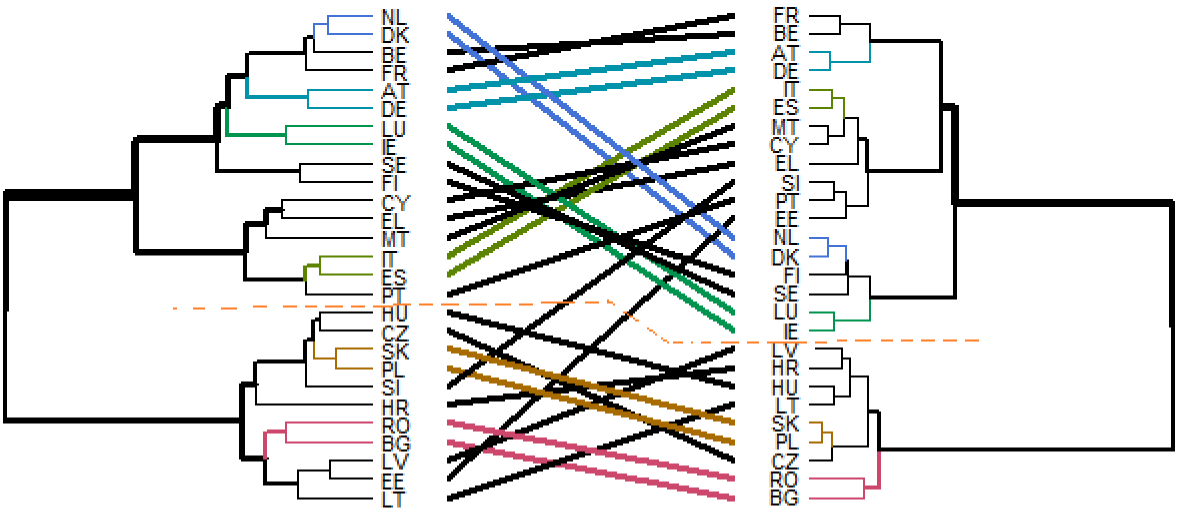

Figure 5. Tanglegram for the comparison of clustering based on 23 indicators and the seven most important indicators
Source: *own calculations*

When clustering based on all indicators, the second cluster contains all post-socialist countries. When grouped based on the top seven, Estonia and Slovenia were placed in the first group. Bulgaria, Romania, Czech Republic, Poland, Slovakia, Lithuania, Hungary, Croatia, and Latvia are in the second cluster.

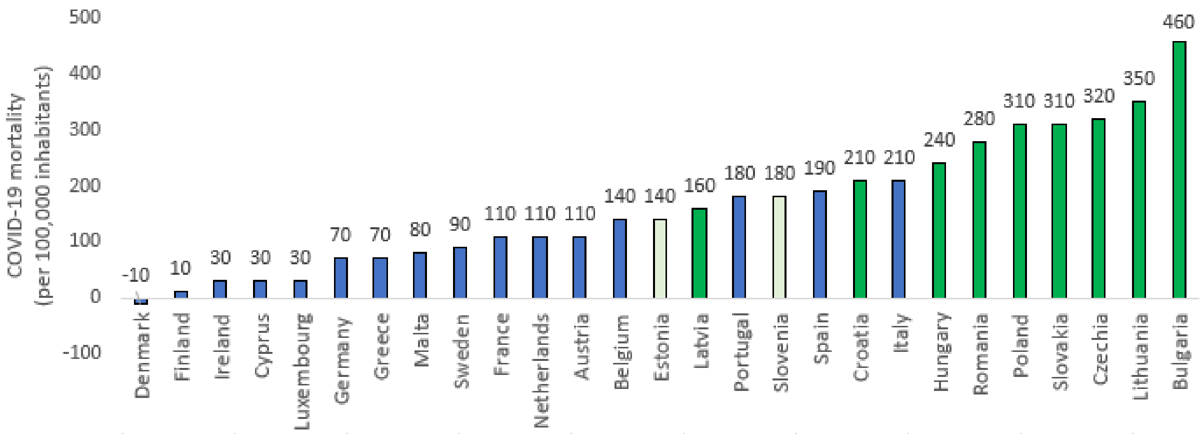

Figure 6. COVID-19 mortality in EU countries
Source*: own representation of excess mortality data (Emort100) by Karlinsky and Kobak (2021)*

The average death rate from COVID-19 is almost triple in the countries of the second cluster (293.3 460 per 100,000 inhabitants) and in the countries of the first cluster (98.9460 per 100,000 inhabitants). COVID-19 mortality was highest in Bulgaria (460 per 100,000 inhabitants), Lithuania (350), Czechia (320), Slovakia and Poland (310), Romania (280). The lowest in Denmark (-10), Finland (10), Ireland, Cyprus, Luxembourg (30). The Mediterranean countries of Italy (210), Spain (190) and Portugal (180) also had similarly high values of COVID-19 mortality as the former socialist states. Hypothesis H2, that COVID-19 mortality is higher in post-socialist states, was partially confirmed.
Table 5 shows the average values of individual indicators for both clusters.

Table 5. Average values of the indicators in clusters (according to the seven most important indicators)

Indicator	1st cluster	2nd cluster	Indicator	1st cluster	2nd cluster	Indicator	1st cluster	2nd cluster
Mcircul	32,4	50,4	Nurses	9,1	6,2	HDD	2566,6	2782,4
AvoidableMort	210,1	420,0	Rural	21,8	35,2	Respir	3,6	3,5
LnGDP	10,4	10,0	Mresp	8,9	5,4	AgeMore65	19,4	19,2
Hbeds	4,2	6,4	HVeryGood	25,0	17,6	OSI20	81,0	80,1
AcutBeds	3,4	4,4	HExp	9,0	6,8	Physicians	4,0	3,5
Blood	20,1	28,6	Obese	18,1	19,2	LnDensity	4,8	4,4
GHSI	77,1	68,0	Smoker	21,9	27,1	Mdiabetes	2,5	2,3
Emort100	98,9	293,3	CDD	166,4	88,7	Diabetes	6,8	7,6

Source: *own calculations*

The most significant factor influencing the incidence of COVID-19 is the rate of death due to diseases of the circulatory system. The rate of death due to diseases of the circulatory system in EU countries decreases from east to west. The countries Bulgaria, Hungary, Romania and the three Baltic member states have the highest share. They have above average values of Rate of death due to diseases of circulatory system. States in the second cluster have an average value of this indicator of 50.4 compared to 32.4 for the countries of the first cluster. The highest value has Hungary (49.4), Estonia (50.9), Latvia (55.2), Lithuania (55.9), Romania (57.1) and Bulgaria (65.8). Spain (28.2), Belgium (26.3), Netherlands (25.0), France (24.3) and Denmark (22.6) have the lowest values.

Despite the significant progress in medicine over the last few decades, Diseases of the circulatory system remain the most common cause of death in the European Union. The burden of Diseases of the circulatory system is not only a health problem, but a huge economic challenge for the health care systems of EU countries. The most recent data estimate that CVD costs the EU economy approximately €210 billion (European Society of Cardiology, 2022). From a medical point of view, acute cardiac injury is a common extrapulmonary manifestation of COVID-19 with potential chronic consequences. SARS-CoV-2, the etiologic agent of COVID-19, can infect the heart, vascular tissues, and circulating cells through ACE2 (angiotensin-converting enzyme 2), the host cell receptor for the viral spike protein. (Chung et al 2021).

Only a healthy lifestyle alone, as is often wrongly claimed, cannot solve death due to diseases of the circulatory system. Many heart disorders can be congenital or caused by other diseases. Functional decline due to aging must also be taken into account. By focusing on secondary prevention, it is possible to reduce the impact of the disease. Geographical inequalities in death due to diseases of the circulatory system are significant. EU policies must help create greater health equity in the EU. The concept of socio-economic status includes income level, educational attainment, employment status and environmental socio-economic factors. It is related to cardiovascular disease and can be considered a modifiable risk factor and target of intervention (Timmis et al, 2022) The European Society of Cardiology and the European Heart Network have published a blueprint for European action. (European Society of Cardiology, 2022).

We identified avoidable mortality as the second most important factor. The concept of avoidable mortality is used to measure the contribution of health care to the health of the population. In the countries of the second cluster, it is alarmingly double. The highest values are achieved for Romania (504.13), Hungary (488.54), Latvia (485.06), Lithuania (465.99) and Slovakia (363.52). The value of avoidable mortality for Slovenia is 245.31. The countries Italy (164.86), Sweden (170.18) and Spain (172.5) have the lowest values. The difference between the highest and the lowest value of avoidable mortality in EU is even 339.27 death per 100,000 inhabitants. Due to the complexity of the possible factors (their interaction and possible synergistic effect) that underlie avoidable mortality, we do not attempt to draw conclusions about the reasons. The historical context plays a certain role. Also, Health care expenditure (all financing schemes) as a percentage of GDP is of importance. The average percentage is higher in the countries of the first cluster (9.0 versus 6.8) and, moreover, from higher GDP.

The third most important indicator is GDP per capita in purchasing power parity. It acquires lower values for the cluster containing almost all former socialist states. The average value for the countries of the first cluster is almost 33,000 Euros, for the second cluster it is one third lower - 22,000 Euros.

The importance of the HBeds and AcuBeds indicators is consistent with the findings presented in the literature review. Both methods determined the importance of the number of hospital beds and acute care hospital beds per 1,000 inhabitants.

Number of hospital beds (per 1,000 people) in the European Union has been gradually decreasing since 1990. In the last 15 years, healthcare reforms have been implemented throughout the EU aimed at rationalizing the use and provision of hospital care, improving its quality and reducing its costs. In most European countries, these policies led to changes in the management of patients in hospitals and were associated with a reduction in the number of hospital beds and acute care hospital beds. According to Garel and Notarangelo (2020), the number of hospital beds decreased by 14% between 2006 and 2016 (a decrease of up to 41% in Finland, a decrease of 3% in Germany).

The general capacity of hospital beds (HBeds) is important, acute care hospital beds (AcuBeds) were the primary source of care for critically ill patients during the COVID-19 pandemic. Although the Oxford Stringency Index, which quantifies the stringency of government policies during COVID, was not ranked among the most important indicators, it was government policies that allowed the peak of the pandemic to shift in time and thus allowed for an increase in the number of HBeds and AcuBeds, thereby contributing to the improvement of care for critically ill patients. However, the role of the nursing staff was often forgotten.

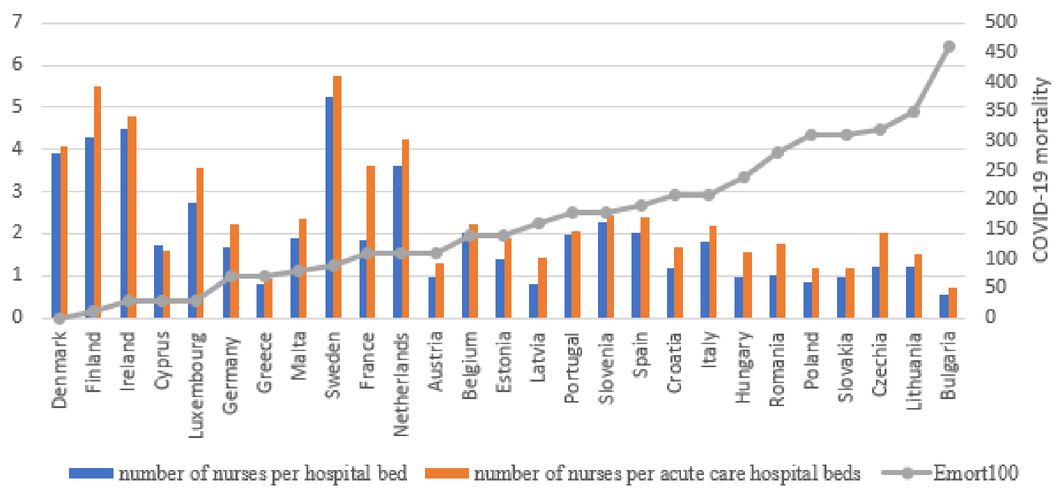

Figure 7. Number of nurses per hospital bed, per acute care hospital bed and COVID-19 mortality
Source: *own representation*

Nurses play an important role in providing care directly to patients. Increasing the number of nurses is not easy - nurses undergo extensive education and special training. Assigning an increasing number of beds ultimately compromises the nurse's ability to provide safe patient care. A study by Lasater et al (2021) reported that each additional patient added to a nurse's workload is associated with an increased risk of in-hospital death.

The number of hospital beds and acute care hospital beds per 1,000 inhabitants is higher in the countries belonging to the second cluster (6.4) than in the countries of the first cluster (4.2). The average number of nurses per 1,000 inhabitants is 9.1 in the countries of the first cluster and a third less (6.2) in the countries of the second cluster. In Bulgaria, there are 1.75 hospital beds per nurse. In Latvia, Greece, Poland it is 1.2 hospital beds. In Sweden, Ireland, Finland, there are about 5 nurses per hospital bed. Thus, the quality of treatment is higher in the countries of the first cluster than in the countries of the second cluster. As can be seen from Figure 7, higher COVID-19 mortality is also attributed to the low number of nurses per hospital bed, or acute care hospital beds (with the exception of Greece).

The Global Health Security Index took seventh place when using the random forest method (10th in the case of the beta coefficient). The performance of the health system to cope with a pandemic like COVID-19 is not sufficient. It must be fast and efficient. The average value of the GHSI was higher for the countries of the first cluster - 77.58 than for the countries of the second cluster - 69.01.

The EU's response to the Covid-19 pandemic began with confusion and chaos. Despite the fact that the Action Plan to enhance preparedness against chemical, biological, radiological and nuclear security risk was adopted in 2017, in 2001 the European Commission established the EU Civil Protection Mechanism. The EU is aware of the importance of preparedness. The European Commission has modernized the EU's civil protection mechanism and created rescEU to strengthen and strengthen the EU's disaster risk management components. stocks of medical facilities in 9 EU member states enable a faster response to health crises (European Commission, 2022).

Treating high blood pressure prevents stroke, heart attack, kidney damage, and heart failure. Chronic diseases are the leading cause of mortality and morbidity in Europe (Busse, Scheller-Kreinsen and Zentner, 2010). Programs aimed at effective management of hypertension will have a significant impact on population health (Whitworth, 2003). states that in the case of optimized hypertension control, cardiac mortality would decline by 49% and cerebrovascular mortality by 62%. The percentage of persons reporting a chronic disease high blood pressure is higher in former socialist countries (except Romania - 15.7). Among developed countries, they are high in Germany (26.2), Portugal (26.6), Finland (27.3).

The severity of government policies as a response to COVID-19 did rank last (in the case of beta coefficients) and fourth from the bottom in the case of random forest. The average stringency of government policies was almost the same for both clusters (81.0 and 80.1). The average for the entire EU, 80.73, was very little different from the median (81.48). Even the skewness coefficient (-0.09) indicates that the probability distribution of this indicator is almost symmetrical. However, the measures evaluated using OSI made it possible to gain time to prepare the material equipment of the healthcare system for the pandemic. When timed well, they contributed to reducing mortality.

The subject's self-assessment of his health status is a frequently used summary indicator of health status. The average percentage of inhabitants Self-perceived health as very good in the countries of the second cluster is lower (17.6) than in the countries of the first cluster (25.0). It is known from studies that the COVID-19 mortality rates for the age group 65 and over are higher. The average value of the proportion of population aged 65 and over is approximately the same in both clusters (19.4 and 19.2). This means that the higher COVID-19 mortality in the second cluster cannot be caused by a higher proportion of the population aged 65 and over. For completeness, it should be recalled that this is not equivalent to saying that the proportion of deaths aged 65 and over is the same in both clusters.

In conclusion, we will comment on individual hypotheses. Hypothesis H1 was confirmed, that only selected indicators are needed to create a good model of mortality dependence on COVID-19. Hypothesis 2, that COVID-19 mortality is higher in post-socialist states, was partially confirmed. Among the countries with high COVID-19 mortality are also the three Mediterranean countries Italy, Spain and Portugal. Hypothesis 3, that the values of factors determining COVID-19 mortality are worse in the post-socialist countries of the EU than in the rest of the EU, with the exception of the factor's available beds in hospitals per 1,000 inhabitants and acute care hospital beds per 1,000 inhabitants. On the other hand, it should be added that the number of nurses per hospital bed and number of nurses per acute care hospital beds are significantly lower, which may contribute to an increase in mortality in general.

Conclusion

The outbreak of the COVID-19 disease shows us that it is necessary to invest in health promotion to strengthen the preparedness, response capacity, and resilience of our health systems. Deaths during the COVID-19 pandemic have exposed and exacerbated long-standing health disparities. Eastern European countries have been hit hard by the inefficiency of their health systems. This paper has identified several significant risk factors associated with mortality from COVID-19.

Mortality from COVID-19 is highly concentrated geographically. The average death rate from COVID-19 in the countries of the second cluster (Bulgaria, Romania, Czech Republic, Poland, Slovakia, Lithuania, Hungary, Croatia, Latvia) is almost three times higher than in the rest of the EU. The results show large differences in the population's health in the countries of the former socialist bloc and the rest of the EU. Avoidable mortality is significantly higher in these countries. Not only is PPP's GDP per capita lower, but it also depends on how these resources are allocated and to try to invest more resources in public health, disease prevention, and medical advances. The health system of these countries is less efficient, and its preparedness is lower.

It has been confirmed that the determinants of health, in a broader sense, are also the economic conditions in which people live. Addressing wider socio-economic inequalities is a key part of reducing health inequalities.

Coordinated and systematic measures are needed to address the causes of health inequalities. There is a need to reduce healthcare disparities between countries within the EU cohesion policy, also in preparedness, recovery, and resilience through the Recovery and Resilience Support Mechanism, the rescEU program, and the new EU4Health health programme.

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