Impact of Russian War on COVID-19 Dynamics in Germany: the Simulation Study by Statistical Machine Learning

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Abstract

The new coronavirus COVID-19 has been spreading worldwide for almost three years. The global community has developed effective measures to contain and control the pandemic. However, new factors are emerging that are driving the dynamics of COVID-19. One of these factors was the escalation of Russia's war in Ukraine. This study aims to test the hypothesis of the influence of migration flows caused by the Russian war in Ukraine on the dynamics of the epidemic process in Germany. For this, a model of the COVID-19 epidemic process was built based on the polynomial regression method. The model's adequacy was tested 30 days before the start of the escalation of the Russian war in Ukraine. To assess the impact of the war on the dynamics of COVID-19, the model was used to calculate the forecast of cumulative new and fatal cases of COVID-19 in Germany in the first 30 days after the start of the escalation of the Russian war in Ukraine. Modeling showed that migration flows from Ukraine are not a critical factor in the growth of the dynamics of the incidence of COVID-19 in Germany, but they influenced the number of cases. The next stage of the study is the development of more complex models for a detailed analysis of population dynamics, identifying factors influencing the epidemic process in the context of the Russian war in Ukraine, and assessing their information content.

Keywords 1

Epidemic model, machine learning, polynomial regression, war, COVID-19, infectious disease simulation

1. Introduction

Coronavirus infection (COVID-19) is an infectious disease caused by the SARS-CoV-2 virus. The outbreak was first reported in Wuhan, China, in December 2019. On January 30, 2020, the World Health Organization declared this outbreak a public health emergency of international concern. Moreover, on March 11, 2020, a global pandemic was declared [1]. At the end of September 2022, almost 620.8 million cases were registered worldwide, 6.5 million of which ended in death [2].

The COVID-19 pandemic in Germany has been observed since the end of January 2020. As of September 2022, four waves of infection were observed, and the fifth one is still ongoing [3]. High mortality was observed during the first two waves, as older age groups were affected [4]. During the third and fourth waves of morbidity, the healthcare system responded effectively by increasing the number of beds and intensive care beds [5]. In November 2020, Germany's national vaccination strategy was adopted and started on December 26, 2020 [6]. At the end of September 2022, 33 million cases of COVID-19 were registered in Germany, of which almost 150 thousand were fatal [2]. Almost 65 million people were vaccinated, 76.77% of the population, 75.21%, received the full vaccination course, and 70.44% received a booster dose [7].

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The escalation of the Russian war in Ukraine, launched on February 24, 2022, caused destruction, human casualties, and a humanitarian crisis. The military invasion also affected the healthcare system in Ukraine. Factors stimulating the spread of infectious diseases have also increased. The temporary occupation of the territories of Ukraine by Russia and active hostilities stimulated migration flows both within the country and to neighboring countries. As of September 2022, 7.4 million refugees from Ukraine were registered in Europe, and 4.13 million citizens of Ukraine received the status of temporary protection in the countries of the European Union [8]. More than 1 million refugees from Ukraine are registered in Germany, and more than 700,000 have received temporary protection status. The migration of the population, as well as the conditions for the evacuation of refugees in Ukraine, is an essential factor that affects infectious disease dynamics.

The COVID-19 pandemic has not only become a challenge for healthcare systems worldwide but also stimulated research in the direction of data-driven medicine and public health informatics. Such studies are aimed at automated medical diagnostics [9], analysis of social [10, 11] and natural [12] factors on the dynamics of the epidemic process, analysis of medical data [13], analysis of medical images [14], studies of molecular structures [15] and nanostructures [16], etc. Machine learning methods have shown high accuracy and efficiency in modeling epidemic processes.

The study aims to test the hypothesis of the influence of migration flows caused by the escalation of the Russian war in Ukraine on the dynamics of the COVID-19 epidemic process in Germany. For this purpose, a model of the COVID-19 epidemic process based on the polynomial regression method was developed and analyzed.

Given research is part of a complex, intelligent information system for epidemiological diagnostics, the concept of which is discussed in [17].

2. Materials and Methods

To test the hypothesis of the impact of migration flows from Ukraine caused by the Russian military invasion on the dynamics of the COVID-19 epidemic process in Germany, the following methodology is proposed:

- To build a simulation model of the COVID-19 epidemic process based on the simplest machine learning method.
- To check the adequacy of the developed model by constructing the predictive dynamics of the COVID-19 epidemic process in Germany for 30 days before the start of the escalation of the Russian war in Ukraine.
- To build a forecast of the dynamics of the COVID-19 epidemic process in Germany for 30 days after the start of the escalation of the Russian war in Ukraine.
- To estimate deviations of the forecast compared to actual data. To compare forecasting errors before and after the start of the escalation of the Russian war in Ukraine for different periods of forecasting.

Since the purpose of the study is only a preliminary test of the hypothesis about the impact of migration on the dynamics of COVID-19, one of the simplest statistical machine learning methods, polynomial regression, was chosen as a simulation model.

Statistical machine learning methods, although simple, have shown high efficiency in modeling and studying the epidemic process of COVID-19. Thus, in the article [18], using statistical machine learning methods, the importance of demographic and clinical variables for mortality from COVID-19 is studied. The authors of [19] propose a model based on statistical machine learning methods to automatically assess the severity of COVID-19 based on clinical and paraclinical characteristics, such as serum levels of zinc, calcium, and vitamin D. The study [20] aims to use statistical machine learning to identify high-risk patients with a slowly progressive and rapidly worsening course of COVID-19 in order to avoid missing a therapeutic intervention, which will prevent medical complications. The authors of [21] explore the features and policies most important for achieving the vaccination threshold using statistical machine learning models for three different specifications, including all US states. Article [22] uses statistical machine learning to identify among the routinely tested clinical and analytical parameters those that would identify patients with the highest risk of death from COVID-19.

Polynomial regression can be used in mathematical statistics when modeling the trend components of time series [23]. The purpose of building a polynomial regression model in the field of time series is forecasting. In the general case, the polynomial equation has the form:

$$y = \sum_{j=0}^{k} b_j x^j, \tag{1}$$

where x_i is the independent variable, y_i is the dependent variable, b_j are the polynomial parameters, and b_0 is the free term.

Polynomial regression models only the trend component of the time series. The parameters of the regression model polynomial are found by the least squares method.

With polynomial regression, you can model non-linear relationships between variables and predict non-linear functions. Various functions can be used to find the polynomial and tun the model. However, polynomial regression is not a universal tool because outliers in the data can significantly affect the simulation result. Also, polynomial regression models are subject to overfitting, so their generalization is difficult outside the data used. Nevertheless, the polynomial regression model is an effective tool for preliminary research and identifying trends in forecasting.

To evaluate the performance of the simulation model, mean absolute percentage errors were calculated:

$$MAPE = \frac{100\,\%}{n} \sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right|, \tag{2}$$

where A_t is the actual value, F_t is the forecast value, and n is number of observations.

3. Results

For the experimental study, a model of the COVID-19 epidemic process was built based on the polynomial regression method. To train the model, we used data on cumulative morbidity and mortality from COVID-19 in Germany provided by the World Health Organization Coronavirus Dashboard [7]. To test the adequacy of the model, forecasts of cumulative new and fatal cases of COVID-19 in Germany were built for 30 days before the start of the escalation of the Russian war in Ukraine. The forecast for cumulative new cases of COVID-19 in Germany from January 25, 2022, to February 23, 2022, is presented in Figure 1.

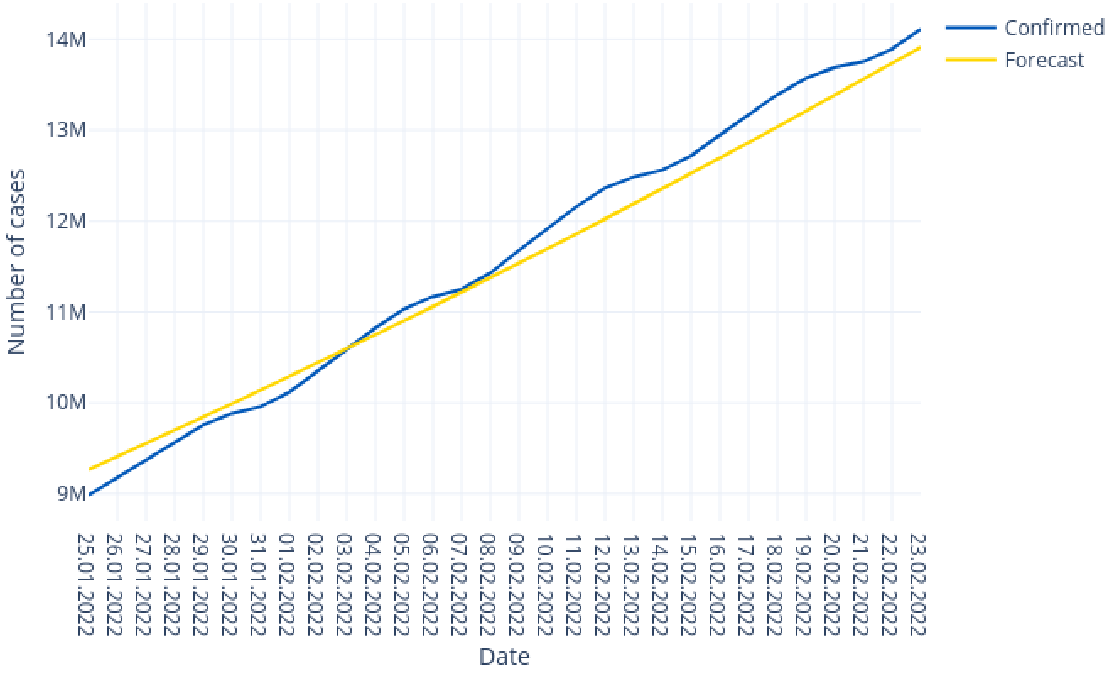

Figure 1: Forecast of COVID-19 cumulative new cases in Germany (25.01.2022 – 23.02.2022).

The forecast for cumulative fatal cases of COVID-19 in Germany from January 25, 2022, to February 23, 2022, is shown in Figure 2. The model's accuracy for the period from January 25, 2022, to February 23, 2022, is presented in Table 1.

Table 1
MAPE of forecast of COVID-19 dynamics in Germany (25.01.2022 – 23.02.2022)

Duration of forecast	New cases	Dead cases
7 days	1.819 %	0.044 %
10 days	1.545 %	0.053 %
20 days	1.492 %	0.201 %
30 days	1.633 %	0.355 %

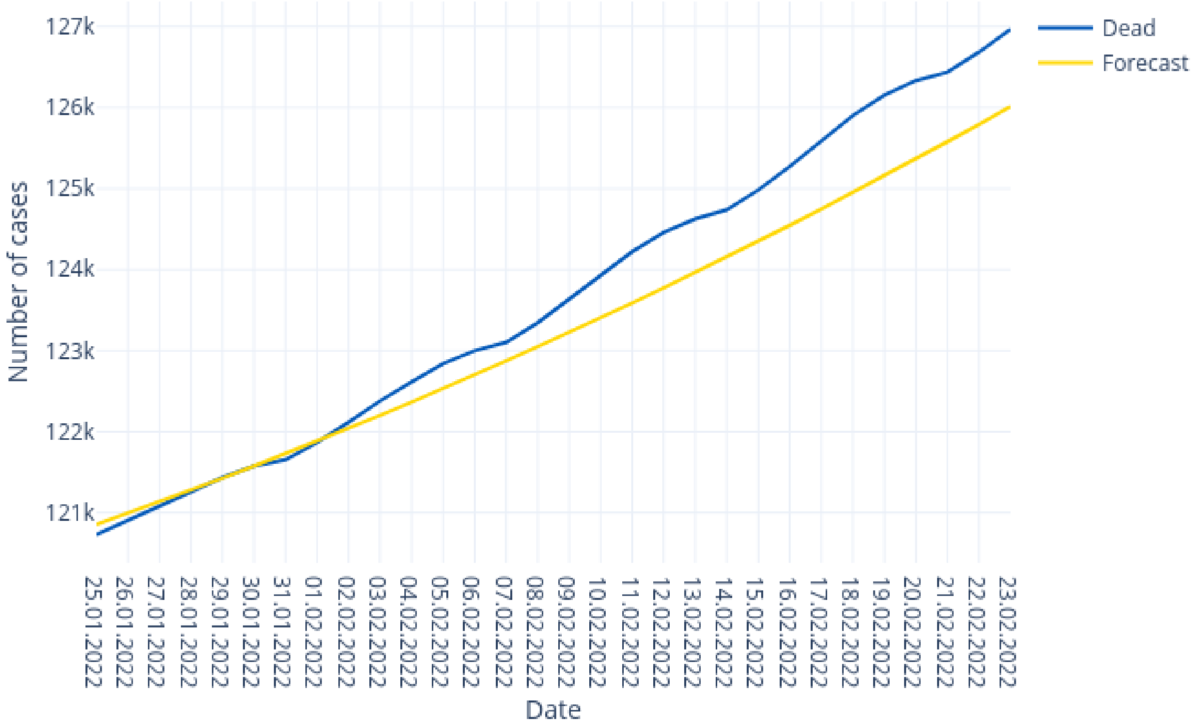

Figure 2: Forecast of COVID-19 cumulative fatal cases in Germany (25.01.2022 – 23.02.2022).

To assess the impact of migration flows on the dynamics of the epidemic process of COVID-19 in Germany, forecasts of cumulative new and fatal cases of COVID-19 in Germany were built for 30 days after the start of the escalation of the Russian war in Ukraine. The forecast for cumulative new cases of COVID-19 in Germany from February 24, 2022, to March 25, 2022, is presented in Figure 3.

The forecast for cumulative fatal cases of COVID-19 in Germany from February 24, 2022, to March 25, 2022, is shown in Figure 4.

The model's accuracy for the period from February 24, 2022, to March 25, 2022, is presented in Table 2.

Table 2
MAPE of forecast of COVID-19 dynamics in Germany (24.02.2022 – 23.03.2022)

Duration of forecast	New cases	Dead cases
7 days	2.722 %	0.159 %
10 days	3.139 %	0.209 %
20 days	4.194 %	0.374 %
30 days	4.258 %	0.408 %

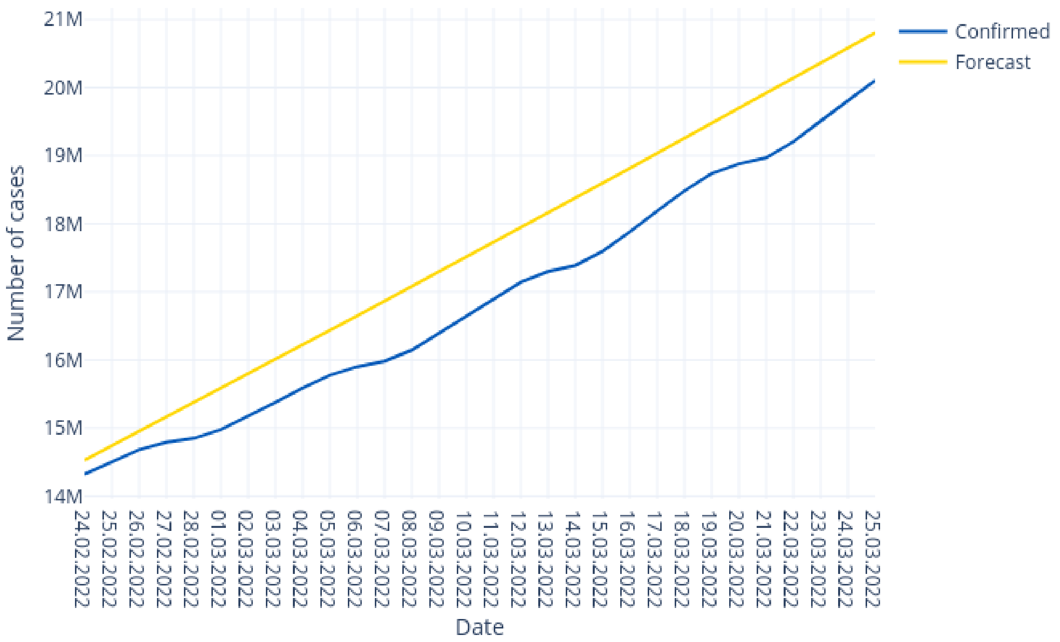

Figure 3: Forecast of COVID-19 cumulative new cases in Germany (24.02.2022 – 25.03.2022).

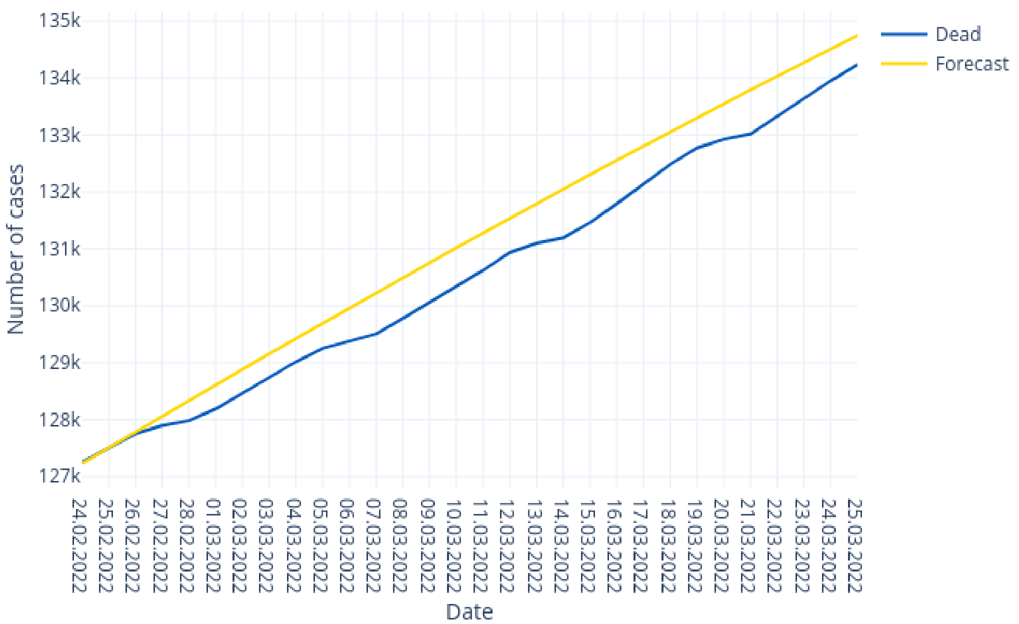

Figure 4: Forecast of COVID-19 cumulative fatal cases in Germany (24.02.2022 – 25.03.2022).

An assessment of the accuracy of the predictive dynamics of COVID-19 in Germany showed high adequacy of the model. At the same time, similar model accuracy is observed when predicting cumulative lethal cases 30 days before the start of the Russian war in Ukraine escalation and 30 days after the start of the escalation of the war. The accuracy of predictive cumulative new cases of COVID-19 in Germany is lower after the start of the escalation of the Russian war in Ukraine. At the same time, the forecast of new cases after the start of the evacuation of Ukrainian residents to Germany still shows high accuracy, from 95.7% for a 30-day forecast to 97.3% for a 7-day forecast. This suggests that the constructed model can be used in public health practice. However, the accuracy of the forecast after the escalation of the Russian war in Ukraine is lower than before the escalation of the war, which suggests that the migration flow of refugees from Ukraine is one of the factors that influenced the dynamics of the COVID-19 epidemic process in Germany. However, the lack of changes in the accuracy of deaths suggests that the migration of refugees from Ukraine to Germany, in general, did not affect the epidemic situation regarding the incidence of COVID-19 in Germany.

Figure 5 shows the deviation of the forecast of daily new cases of COVID-19 in Germany from the actual data from February 24, 2022, to March 25, 2022.

Figure 6 shows the deviation of the forecast of daily COVID-19 deaths in Germany from the actual data from February 24, 2022, to March 25, 2022.

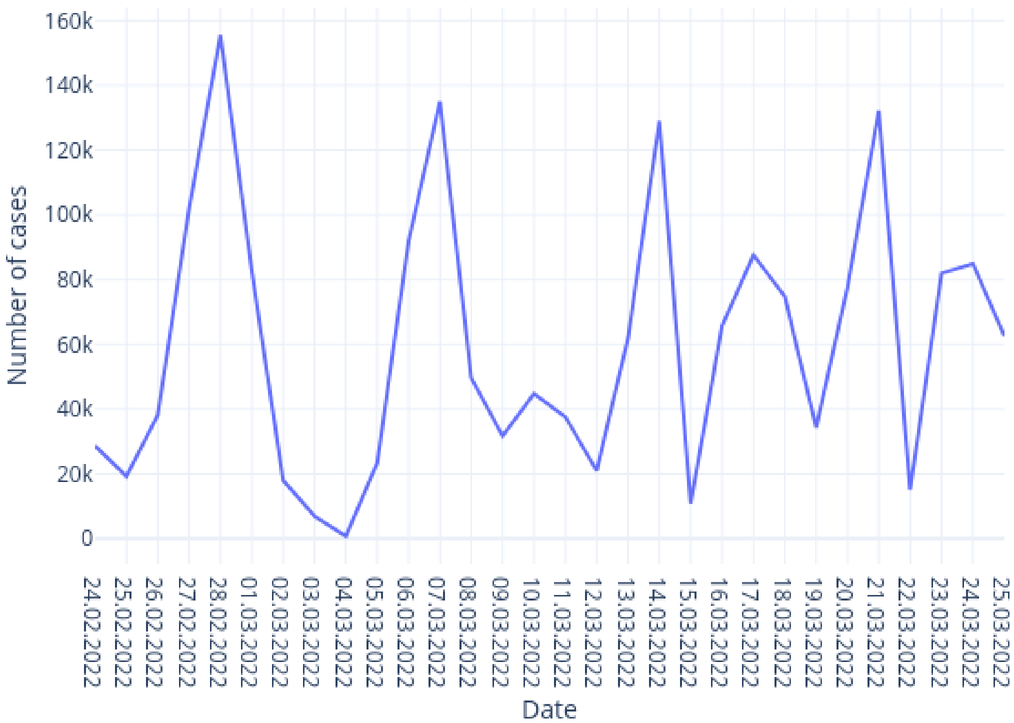

Figure 5: Deviation of the forecast of COVID-19 cumulative new cases in Germany from the actual statistics (24.02.2022 – 25.03.2022).

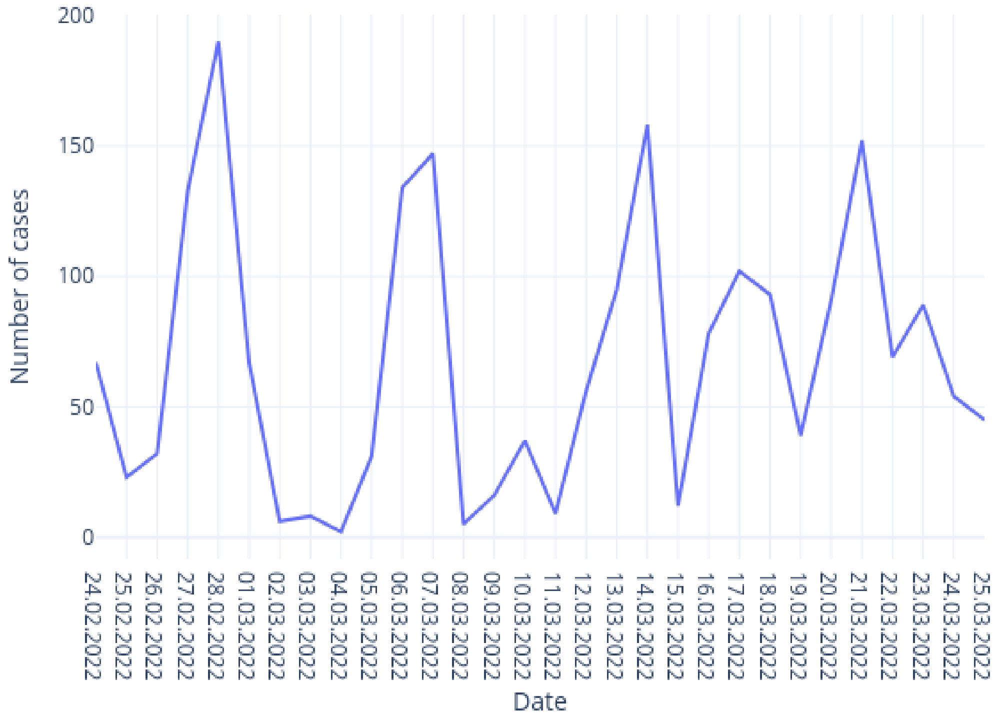

Figure 6: Deviation of the forecast of COVID-19 cumulative fatal cases in Germany from the actual statistics (24.02.2022 – 25.03.2022).

4. Conclusions

The escalation of the Russian war in Ukraine stimulated the spread of infectious diseases. Among the factors that contribute to the worsening of the epidemic situation are the difficulty in obtaining medical care in areas with active hostilities, the redistribution of healthcare system resources for the needs of the army and to help the affected civilian population, the high population density while in bomb shelters, the mental replacement of the COVID-19 problem with survival during the war, etc. An important factor influencing the dynamics of infectious diseases is population migration. At the same time, this process is essential in war conditions. People were evacuated from the temporarily occupied territories and territories with active hostilities in overcrowded trains without observing anti-epidemic rules. When crossing the border with the countries of the European Union, there was a considerable population crowding. Medical records and vaccination information were not checked.

At the beginning of the escalation of the war, in Ukraine there was an increase in the incidence of COVID-19 caused by the Omicron strain. The COVID-19 vaccine campaign in Ukraine began exactly one year before Russia's full-scale invasion. As of February 2022, the number of those vaccinated in Ukraine was 38.24%, 36.96% completed the full vaccination course, and only 1.76% of the population received a booster dose. This was the lowest vaccination rate among European countries.

To test the hypothesis about the impact of migration flows caused by the escalation of the Russian war in Ukraine on the dynamics of the COVID-19 epidemic process in Germany, a machine learning model was developed based on the polynomial regression method. To assess the adequacy of the model, forecasts of cumulative new cases and cumulative fatal cases of COVID-19 in Germany were built 30 days before the escalation of the Russian war in Ukraine. The model showed high accuracy from 98.18% to 98.5% for cumulative new cases and from 99.65% to 99.96% for cumulative fatal cases, depending on the forecast period.

To assess the impact of migration on the dynamics of COVID-19, the model was applied to data on the dynamics of the epidemic process of COVID-19 in Germany for 30 days after the start of the escalation of the Russian war in Ukraine. The model also showed high accuracy from 95.74% to 97.28% for cumulative new cases and from 99.59% to 99.84% for cumulative fatal cases, depending on the forecast period.

Although the model showed high forecasting accuracy for both forecast periods, the accuracy of predicting cumulative new cases of COVID-19 in Germany after the start of the escalation of the Russian war in Ukraine became lower than before the escalation of the war. This suggests that the migration of the population from Ukraine to Germany influenced the dynamics of the COVID-19 epidemic process, although it did not become a decisive factor. However, the lack of deterioration in model adequacy for cumulative deaths from COVID-19 in Germany after the Russian military invasion of Ukraine suggests that, in general, migration flows have not changed the epidemic situation regarding COVID-19 in Germany.

Future research will focus on building more complex simulation models of the COVID-19 epidemic process to assess the information content of specific factors caused by the escalation of the Russian war in Ukraine that affect the dynamics of the epidemic process of infectious diseases.

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