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Mykola BUTKEVYCH[1], Ievgen MENIAILOV[2], Yaroslav LUTSIV[3], Bohdan KRAIVSKYI[3], Dmytro CHUMACHENKO[1, 4]

[1] *National Aerospace University "Kharkiv Aviation Institute", Kharkiv, Ukraine*
[2] *V.N. Karazin Kharkiv National University, Kharkiv, Ukraine*
[3] *O.M. Beketov National University of Urban Economy in Kharkiv, Kharkiv, Ukraine*
[4] *Max Planck Institute for Demographic Research, Rostock, Germany*

WAR-DRIVEN DISPLACEMENT AND COVID-19 IN POLAND: SIMULATION STUDY USING LSTM MODEL

Russia's full-scale invasion of Ukraine led to Europe's largest and fastest displacement since World War II. Poland received the largest inflow. Rapid movement can affect COVID-19 spread and stress testing, reporting, and vaccination systems. ***Aim:*** *To evaluate whether the invasion-related displacement coincided with short-term departures in Poland's national COVID-19 cases and deaths using an intervention-anchored counterfactual forecasting approach learned from pre-invasion trends.* ***Object of the study:*** *Daily COVID-19 cases and deaths in Poland. Data come from the WHO dashboard, which spans May 2020 and centers on the 24 February 2022 invasion with a 30-day post-invasion horizon.* ***Methods:*** *We fit a univariate stacked LSTM to pre-invasion data and forecast one step ahead for the first 30 days after 24 February 2022. The network uses LSTM(128) - LSTM(64) - Dense(25) - Dense(1) with a linear output. The timeline is split into training (before 24 January 2022), validation (24 January-23 February 2022), and testing (24 February-+30 days). Each series (cases, deaths) fits six times with different random starts. Accuracy is measured using the mean absolute percentage error (MAPE). Deviations from the counterfactual are summarized as absolute and relative effects over the 30-day window.* ***Results:*** *Observed daily values closely tracked the counterfactual during the first month after the invasion, with only modest, short-lived over-prediction in the middle of the window. Between the validation and test periods, the average MAPE rose from 5.94% to 14.39% for cases and from 5.90% to 14.62% for deaths, reflecting greater short-run uncertainty but no large national-level break.* ***Conclusion:*** *Despite exceptional migration pressure, Poland's national COVID-19 series did not show a marked divergence from a data-driven counterfactual in the first month after 24 February 2022.* ***Scientific novelty:*** *To the best of our knowledge, this study provides the first Poland-focused, short-horizon, data-driven counterfactual of the invasion shock under real-world Omicron conditions. It uses a simple, transparent LSTM trained only on pre-shock national data, repeats fits to capture training variability, and quantifies departures with clear absolute and relative measures.*

Keywords: *epidemic model; epidemic process; epidemic simulation; simulation; deep learning; LSTM; war.*

1. Introduction

Large-scale emergencies reshape infectious disease dynamics by disrupting health systems, altering contact patterns, and driving sudden population movements. Conflicts and disasters interrupt routine surveillance and prevention, reduce access to diagnosis and care, and create conditions favoring respiratory pathogen transmission in shelters, transport hubs, and crowded housing [1]. Recent studies have underscored that conflict settings experience a higher burden and faster spread of infectious diseases, including COVID-19, precisely because mobility increases while public health capacity contracts [2].

Russia's full-scale invasion of Ukraine on 24 February 2022 triggered one of the largest and fastest displacement events in Europe since World War II, with Poland serving as the principal entry point and host during the first year. Between 24 February 2022 and 24 February 2023, more than 10 million border crossings from Ukraine into Poland were recorded, primarily by women, children, and older adults, prompting an unprecedented public health response by Polish authorities and civil society [3]. In parallel, Ukraine entered the full-scale war with relatively low COVID-19 vaccination coverage (less than 35% of the population was fully vaccinated by February 2022) [4]. This amplifies concern that cross-border flows could interact with heterogeneous immunity and testing practices to influence epidemic trajectories in receiving countries [5].

The invasion also degraded the health information systems of Ukraine. In early 2022, formal COVID-19 surveillance and routine communicable disease reporting were severely disrupted, creating uncertainty about contemporaneous incidence in places of origin and complicating risk assessment for countries receiving

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refugees [6]. At the same time, Poland rapidly expanded refugees' access to health services. It deployed targeted public health initiatives, yet the short-term epidemiologic impact of the sudden population inflow on Poland's COVID-19 time series remains only partially quantified [7].

Human mobility is a key driver of respiratory infection dynamics, and multiple reviews and modelling studies during the pandemic have shown strong links between movement patterns and epidemic waves [8]. However, mobility data can be incomplete or non-representative, and real-time displacement during crises is especially difficult to capture [9]. Complementing mechanistic reasoning with data-driven approaches that can extract signals from observed surveillance time series is important.

Time-series deep learning offers a pragmatic method for estimating counterfactual trajectories when structural data on contacts, testing policy, and mobility are sparse or unreliable [10]. Long short-term memory (LSTM) networks and related hybrids have repeatedly shown competitive performance for forecasting COVID-19 cases across diverse settings, capturing nonlinearities and regime changes without prespecifying the transmission structure [11]. Recent evaluations and reviews, ranging from standalone LSTM and encoder-decoder variants to ARIMA-LSTM ensembles, report improved short-horizon accuracy over classical baselines, supporting their use as empirical tools for policy-relevant nowcasting and scenario comparison [12].

For Central and Eastern Europe, initial commentaries and modelling analyses suggested that refugee flows could have detectable effects on host-country COVID-19 signals [13]. However, robust, country-specific quantification anchored in observed data has been limited. One cross-country analysis using a generalized SIR framework reported short-term departures from the expected trajectories in several Western European countries in March 2022 [14]. However, the model structure and cross-national aggregation raise questions about the magnitude and timing of Poland's level. In Poland, one year later, public health scholars documented the breadth of the response, including legal access to care, vaccination offers, and information campaigns [3]. However, these descriptive accounts did not isolate the net contribution of the February-March 2022 migration shock to the reported incidence.

This study addresses this gap by estimating the short-term impact of population flows caused by the COVID-19 invasion of Poland. Using daily case (and death) series compiled from international surveillance feeds, LSTM-based forecasting models were trained on pre-invasion Polish data to construct counterfactual trajectories and compare them with observed post-invasion outcomes. Focusing on the first month after 24 February 2022, when border crossings peaked, we quantify deviations from the counterfactual and examine their temporal alignment with the displacement wave was examined. Our data-driven design provides mechanistic insights into mobility and vaccination heterogeneity while remaining resilient to Ukraine's upstream reporting instabilities.

The goal and objectives are to develop and evaluate an intervention-anchored, short-horizon counterfactual forecasting pipeline for Poland's national COVID-19 cases and deaths around 24 February 2022 by training a univariate stacked LSTM on pre-invasion data, generating one-step-ahead forecasts for the first 30 days, and assessing deviations with MAPE plus absolute and relative effect measures, as a practical template for rapid post-shock situational assessment.

The paper offers three contributions. First, we present an intervention-anchored counterfactual forecasting setup that trains a univariate stacked LSTM strictly on pre-invasion observations and preserves temporal causality by producing the post-invasion path via one-step-ahead predictions. Second, we provide a transparent evaluation protocol that repeats model fitting across six random initializations, reports out-of-sample MAPE, and summarizes deviations from the counterfactual over the 30-day window using absolute and relative effects. Third, the pipeline is applied to Poland's national COVID-19 time series and the outputs within Poland's refugee-health response and the literature on conflict, mobility, and respiratory epidemics are interpreted.

Section 2 (Current Research Analysis) provides a comprehensive review of recent research on conflicts and epidemiology. Section 3 (Materials and Methods) describes the model and experimental design. Section 4 (Results) applies the model to the spread of COVID-19 in Poland around the Russian full-scale invasion of Ukraine. Section 5 (Discussion) interprets the results and identifies implications for pandemic preparedness. Finally, the Conclusions summarize the theoretical and practical contributions of this study.

2. Current Research Analysis

Since 2022, research at the intersection of forced displacement and respiratory epidemics has expanded. However, key empirical and methodological gaps remain, especially for quantifying how sudden, large-scale cross-border flows shape COVID-19 dynamics in host countries, such as Poland. This section synthesizes the most relevant evidence and outlines where our study has advanced the field.

Multiple reviews have concluded that armed conflict creates conditions, crowding, disrupted health services, interrupted surveillance, and population movements that amplify the transmission of infectious diseases, including COVID-19. A 2024 systematic review catalogued these pathways across settings and stressed the need for preparedness plans that explicitly address disease risks in conflict-affected populations [1]. Evidence specific to migrants and refugees during COVID-19 pandemic indicates a consistently higher risk of infection and severe outcomes than among host populations, although heterogeneity across settings is substantial. The most comprehensive peer-reviewed synthesis to date found elevated infection risk and differences in hospitalization and ICU admission among migrants and forcibly displaced people, reinforcing the importance of inclusive prevention and care [15].

Within the Ukrainian context, early commentaries documented the rapid collapse of routine COVID-19 reporting after 24 February 2022, invasion, complicating real-time situational awareness [16]. Subsequent modeling work projected large epidemic waves under conditions of low vaccination coverage and service disruption [6]. This study highlighted the feasibility and life-saving potential of vaccinating refugees in receiving countries when in-country vaccination is constrained.

Peer-reviewed studies directly estimating the impact of the COVID-19 pandemic on Ukrainian refugee flows in host countries are still scarce. A comparative analysis using a generalized SIR framework inferred short-lived increases in transmission potential in several European countries in March 2022 [14]. For Poland, similar contemporaneous infection prevalence in Ukraine and Poland likely muted any additional growth attributable to inflows. Polish public health syntheses describe an extensive humanitarian response and universal access to COVID-19 vaccination for refugees, but also document low early uptake (e.g., ~35,400 vaccinations by mid-April 2022) and structural barriers, suggesting potential for pockets of susceptibility [3].

Complementary micro-level studies focus on behavioral and access determinants among Ukrainians in Poland. Qualitative research and surveys have identified low vaccination uptake, safety concerns, logistical hurdles, and information gaps as barriers, while underscoring the need for tailored outreach [17]. A broader clinical and genomic characterization of Poland’s epidemic shows that the Omicron BA.1/BA.2 transition dominated early-2022 trends, with marked regional heterogeneity in testing, vaccination, and mortality, background dynamics that any displacement-effect analysis must account for [18]. In parallel, European evidence consistently emphasizes a structural data problem: migrant and refugee variables are often missing from health information systems, limiting the ability to precisely link flows to outcomes [19].

A robust literature ties human mobility to SARS-CoV-2 transmission. Review by N. Kostandova and colleagues of 232 studies documented extensive use of population-level mobility data (e.g., mobile phone-based indicators), generally finding that, albeit with notable methodological variability and bias risks, reduced mobility correlates with reduced transmission [20]. The review also highlighted the lack of standardized approaches to integrate mobility into epidemic analyses. Earlier reviews similarly reported a strong association between changes in mobility and respiratory virus spread [9]. However, very few of these studies isolate the causal effect of exogenous, cross-border displacement shocks on host-country incidence, as opposed to within-country policy-driven mobility changes, leaving an important gap for the Ukraine-Poland case.

Data-driven forecasting has matured. Recent reviews and comparative studies have reported that deep learning models, particularly LSTM variants and hybrids (e.g., ARIMA-LSTM, stacked LSTM-GRU), often match or outperform classical baselines for short-term forecasts while requiring careful handling of nonstationarity and exogenous signals [21]. Large multi-model evaluations covering Germany and Poland during 2020-2021 show that forecast ensembles improve calibration and accuracy, but predictive skill can degrade rapidly beyond 1-2 weeks, an important caveat for attributing effects of sudden population inflows [22].

Contemporaneous variant waves and subnational heterogeneity complicate empirical attribution. Genomic and epidemiological analyses indicate that the BA.1-BA.2 transition drove the early-2022 dynamics of Poland, with regional variation in testing and vaccination correlated with mortality [18]. Independent European surveillance reported lower Omicron severity vs. Delta but very high transmission, implying large, rapidly changing incidence baselines around the time of the refugee influx [23]. Together with incompletely captured migration variables in routine health data, these features create identification problems that prior studies either acknowledge or sidestep [19].

Therefore, to our knowledge, the current research provides the first quantitatively grounded estimate of the short-run effect of the 2022 displacement shock on the incidence of COVID-19 in Poland under real-world Omicron conditions.

3. Materials and Methods

We quantified the short-run impact of the 24 February 2022 shock on Poland’s COVID-19 indicators by learning pre-invasion dynamics from national surveillance time series and projecting a model-based counterfactual into the first post-invasion month. The analysis uses only Poland’s daily series and adheres to

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the attached protocol: observations come from the WHO Coronavirus (COVID-19) Dashboard, the "red line" intervention date is 24 February 2022, records span from the beginning of May 2020, and two dependent variables, daily new positive tests and daily deaths, are retained for Poland [24]. Keeping with the documented data, the WHO series is treated as official but subject to revision and cross-source heterogeneity [25].

Time segmentation follows a three-block timeline centered on the intervention. Let t_0 = 24 January 2022 and t_1 = 24 February 2022. We train on all dates before t_0, tune on the adjacent validation window $[t_0, t_1)$, and reserve $[t_1, t_1+30$ days) exclusively for out-of-sample evaluation and effect estimation. This temporally ordered hold-out approximates the operational nowcasting immediately preceding the shock and aligns with the interrupted time series guidance for evaluating population-level interventions occurring at a clearly defined time point [26].

Forecasts are generated using a stacked LSTM network tailored to univariate regression. The draft topology comprises LSTM(128) – LSTM(64) – Dense(25) – Dense(1), with hyperbolic tangent activation in LSTM units, a hard-sigmoid nonlinearity for recurrent gating, and a linear output appropriate for continuous targets (Figure 1).

Layer (type)	Output Shape
lstm_40 (LSTM)	(None, 1, 128)
lstm_41 (LSTM)	(None, 64)
dense_40 (Dense)	(None, 25)
dense_41 (Dense)	(None, 1)

Figure 1. Model's architecture

We implemented this architecture for each Polish series (cases and deaths). The LSTM cell is defined by the following standard gating equations [27]:

$$
\begin{gathered}
i_t = \sigma(W_i x_t + U_i h_t - 1 + b_i),\\
f_t = \sigma(W_f x_t + U_f h_t - 1 + b_f),\\
\widetilde{c_t} = \tanh(W_c x_t + U_c h_t - 1 + b_c),\\
c_t = f_t \odot c_t - 1 + i_t \odot \widetilde{c_t},\\
o_t = \sigma(W_o x_t + U_o h_t - 1 + b_o),\\
h_t = o_t \odot \tanh(c_t),
\end{gathered}
$$

where $\sigma(\cdot)$ is the logistic function and $\odot$ denotes the Hadamard product. The forget-gate f_t enables irrelevant memory decay, addressing vanishing-gradient behavior in long sequences [28].

Training minimizes mean squared error (MSE) in the pre-intervention data while monitoring the validation MSE at each epoch. The epoch with the best validation score is the final model (Figure 2). Optimization uses Adam with its bias-corrected first and second moment estimates of the stochastic gradient g_t [29]:

$$
\begin{gathered}
m_t = \beta m_t - 1 + (1 - \beta_1) g_t,\\
v_t = \beta_2 v_t - 1 + (1 - \beta_2) g_t \odot 2,\\
\widehat{m_t} = \frac{m_t}{1 - \beta_1^t},\\
\widehat{v_t} = \frac{v_t}{1 - \beta_2^t},\\
w_t + 1 = w_t - \alpha \frac{\widehat{m_t}}{\sqrt{\widehat{v_t}} + \varepsilon}.
\end{gathered}
$$

```
448/448 [==============================] - 1s 2ms/step - loss: 0.0045 - val_loss: 0.0141
Epoch 5/15
448/448 [==============================] - 1s 3ms/step - loss: 0.0036 - val_loss: 0.0165
Epoch 6/15
448/448 [==============================] - 1s 3ms/step - loss: 0.0031 - val_loss: 0.0118
Epoch 7/15
448/448 [==============================] - 1s 3ms/step - loss: 0.0035 - val_loss: 0.0188
Epoch 8/15
448/448 [==============================] - 1s 2ms/step - loss: 0.0032 - val_loss: 0.0107
Epoch 9/15
448/448 [==============================] - 1s 2ms/step - loss: 0.0030 - val_loss: 0.0098
Epoch 10/15
448/448 [==============================] - 1s 3ms/step - loss: 0.0031 - val_loss: 0.0135
Epoch 11/15
448/448 [==============================] - 1s 3ms/step - loss: 0.0030 - val_loss: 0.0090
Epoch 12/15
448/448 [==============================] - 1s 3ms/step - loss: 0.0027 - val_loss: 0.0143
Epoch 13/15
448/448 [==============================] - 1s 3ms/step - loss: 0.0026 - val_loss: 0.0097
Epoch 14/15
448/448 [==============================] - 1s 3ms/step - loss: 0.0025 - val_loss: 0.0094
Epoch 15/15
448/448 [==============================] - 1s 3ms/step - loss: 0.0023 - val_loss: 0.0116
```

Figure 2. Training process

Adam is well-suited to non-stationary, noisy objectives typical of time series epidemics. We adopt default hyperparameters unless stated otherwise in the sensitivity checks.

The counterfactual trajectory for the post-intervention window is the model's one-step-ahead forecast initialized from the last pre-intervention state. Let y_t denote the observed Polish surveillance count. We summarize the absolute "excess" over the first 30 days after 24 February 2022 as follows:

$$\Delta = \sum t = t_1^{t_1+30} (y_t - \hat{y}_t^{cf}),$$

and the corresponding relative effect as

$$\delta = 100 \times \frac{\sum t = t_1^{t_1+30} (y_t - \hat{y}_t^{cf})}{\sum t = t_1^{t_1+30} \hat{y}_t^{cf}}.$$

This interruption-anchored comparison is consistent with ITS logic. It estimates deviations from the extrapolated pre-trend at the point of a population-level shock while remaining fully data-driven. Each Polish series fits six times with different random initializations. We report mean performance across runs and use the run-to-run standard deviation to convey training variability. This repeated-fit practice stabilizes estimates in non-convex neural optimization.Forecast accuracy is evaluated on held-out data using mean absolute percentage error (MAPE). This setup is distinguished by strict pre-intervention training to preserve temporal causality, one-step-ahead counterfactual generation anchored at the intervention date, and repeated model fits to report optimization variability.

4. Results

The LSTM model trained on Poland's pre-invasion series captured the marked weekly seasonality and the broader downward trend from late January to March 2022. Visual inspection of the post-intervention forecasts against held-out observations shows close alignment for both outcomes, with a modest positive bias (model > observed) during the 30-day test window's middle. This observation is consistent with the rapidly changing Omicron conditions observed in March 2022, when BA.2 was taking over the WHO European Region. The WHO case/death series and definitions follow the organization's dashboard specifications.

Figure 3 shows the experimental results for Poland's daily cases: model counterfactual vs. observed. The forecasted "after-shock" trajectory closely tracks the observed counts and reproduces the weekly cycle. Small, transient over-predictions appear in the second and third weeks after 24 February 2022.

Figure 4 shows the experimental results for the daily deaths in Poland: model counterfactual vs. observed. As with cases, the forecast mimics the observed pattern with minor positive bias during mid-window dates.

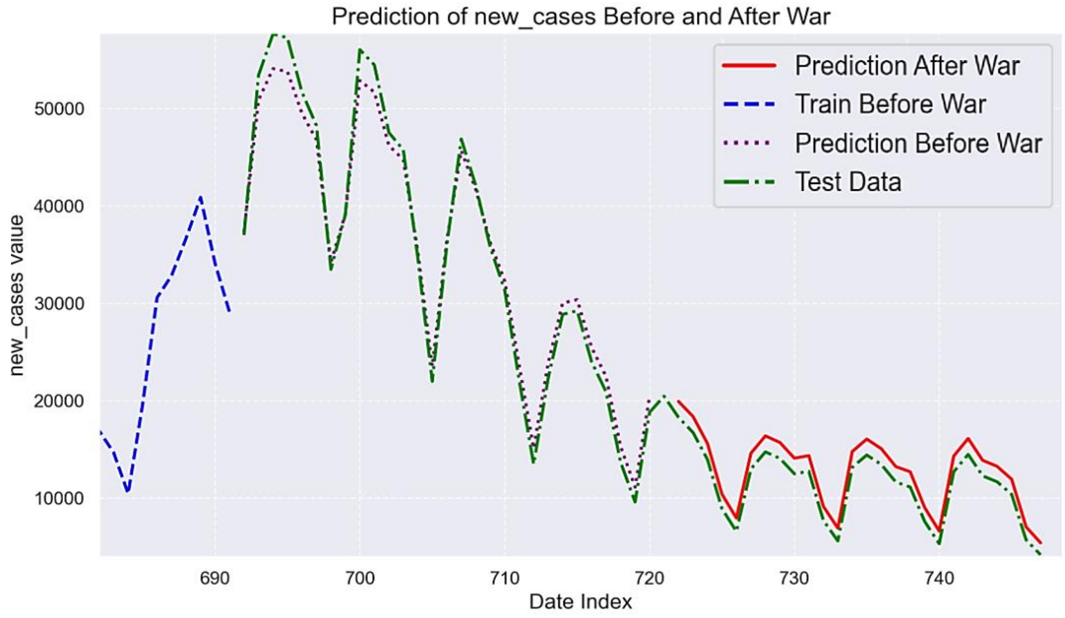

Figure 3. The results for daily cases

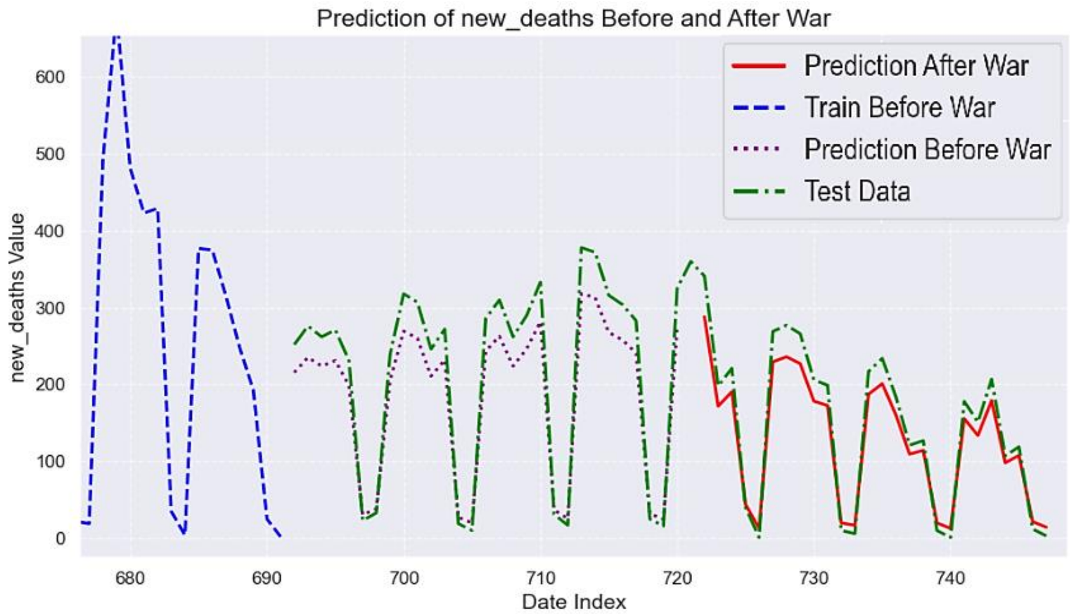

Figure 4. The results for death cases

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Quantitatively, the forecast error increased from the validation (“before”) to the post-intervention (“after”) window, which is expected when projecting across an abrupt regime change. The averages across six independent trainings correspond to absolute percentage error and are summarized in Table 1.

Table 1.

Experimental results (MAPE)

Run	Outcome	Validation (before)	Test (after)
Run 1	Death	7.48	16.32
	Cases	5.81	13.67
Run 2	Death	11.09	21.89
	Cases	6.32	14.09
Run 3	Death	8.04	16.59
	Cases	5.60	15.58
Run 4	Death	2.60	9.54
	Cases	5.04	13.42
Run 5	Death	2.77	10.29
	Cases	6.46	13.01
Run 6	Death	3.39	13.10
	Cases	6.41	16.57
Average	Death	5.90	14.62
	Cases	5.94	14.39

These results indicate that a purely data-driven counterfactual trained on Poland’s pre-invasion trajectory reproduces the near-term post-invasion dynamics with good fidelity at daily resolution. At the same time, the increase in the absolute percentage error after 24 February 2022 reflects the added unpredictability during the transition period from BA.1 to BA.2.

5. Discussion

Our analysis indicates that Poland’s national COVID-19 trajectory during the first 30 days after the Russian full-scale invasion of Ukraine remained close to a counterfactual learned from pre-invasion data, with only modest, transient over-prediction. Epidemiologically, this pattern suggests that an exceptional migration shock did not translate into a large, immediate discontinuity in daily national incidence during a phase of rapid Omicron sublineage turnover and high background transmission.

Variant dynamics are the first and most proximate explanation. Independent genetic-epidemiology work from Poland documented the transition from Delta to Omicron and the sequential rise of BA.1, BA.2, and later BA.5 in early-mid 2022, with regional heterogeneity in timing [30]. Such turnover shifts short-run baselines and reduces the transportability of pre-shock patterns, precisely when our model shows a small, mid-window positive bias. When the incidence is already high and changes quickly because of subvariant replacement, additional introductions or mixing shocks need not create visible step changes at the national scale, even if they affect risk in specific localities.

The migration context further supports a diffuse national signal. Demographic and border-statistics syntheses estimate >8.8 million crossings into Poland from Ukraine and >7 million returns from Poland to Ukraine in 2022, with sustained onward mobility across the EU in subsequent months. Women and children dominated these flows and were widely distributed across Polish regions and EU destinations, which dilutes any single-place, single-time effect on transmission at the national level [31]. As of mid-2025 (27 per 1,000 residents), Eurostat reports around 1.0 million people under temporary protection in Poland, underscoring the magnitude and persistence of displacement while also showing its dispersion [32].

Health system responses likely moderated the short-run transmission consequences. From 24 February 2022, Poland granted people fleeing the war broad access to publicly financed care. It enabled vaccination under national and EU temporary protection frameworks, lowering barriers to primary care and immunization [33]. However, migrant health research across Europe demonstrates that structural and informational barriers persist: a recent systematic review shows that migrants and forcibly displaced people experienced higher infection and worse outcomes than host populations even in later stages of the pandemic [15]. Pan-European surveys of Ukrainian refugees identified difficulties in navigating services and maintaining continuity of care [34]. These realities imply pockets of elevated risk, even if national aggregates remain stable. Polish hospital data independently recorded a sharp post-invasion rise in the number of admissions of Ukrainian patients (from 2 to 22 per day), with the case-mix shifting towards women and children [35]. This demonstrates a systemic impact that would not necessarily manifest as abrupt changes in the national incidence of COVID-19.

These strands suggest a coherent interpretation of the study’s results. Poland’s epidemic signal largely reflected variant-driven baselines at the national level and over a short horizon. Simultaneously, the migration shock was temporally extended, spatially diffused, and partially offset by rapid access to services. None of this negates the likelihood of local effects or equity gaps. On the contrary, elevated vulnerability among displaced populations and documented barriers to access argue for continued targeted vaccination, culturally adapted communication, and low-barrier primary care in reception and settlement areas.

Several limitations frame the inference and point to the next steps. First, univariate national time series cannot absorb exogenous covariates; thus, deviations from counterfactuals are descriptive rather than causal. Second, national aggregation can mask spatial heterogeneity. Third, routine surveillance often lacks standardized migrant identifiers, which hinders linkage and timely attribution. Recent Polish and European initiatives to integrate border-guard, population, education, and insurance registers into an integrated register of refugees illustrate a feasible path to close these gaps and enable public health analytics that are migration-aware.

Policy implications directly follow. Public health monitoring should extend beyond national aggregates to subnational, migration-aware dashboards that combine epidemiologic indicators with high-resolution mobility and settlement data, program data on vaccination and primary care among beneficiaries of temporary protection, and standardized refugee identifiers with strong privacy safeguards. Maintaining broad access to care under temporary protection provisions and investing in tailored uptake strategies remain essential to mitigate concentrated risks that national-level models may not detect.

6. Conclusions

This study used the Polish national time series to estimate a counterfactual COVID-19 trajectory around the full-scale Russian invasion of Ukraine. Over the first 30 days after the shock, the observed incidence closely tracked forecasts learned on pre-invasion dynamics. Any deviations were modest and transient. Interpreted in context, this pattern is consistent with a period of rapid Omicron sublineage turnover, with BA.2 having a documented growth advantage over BA.1, which shifts short-run baselines and can mute the national-level signal of an external shock.

Methodologically, the study operationalizes an ITS-compatible, pre-shock–trained LSTM counterfactual with transparent deviation metrics. Practically, it provides a reproducible framework to guide early post-shock surveillance and reinforces the need for the already outlined subnational, migration-aware monitoring steps.

This study provides a Poland-specific, data-driven counterfactual for the immediate post-invasion month, isolating short-run effects under real-world Omicron conditions while avoiding cross-country pooling. Framing the migration shock against contemporaneous variant dynamics and policy context adds a disciplined interpretation.

Despite the largest displacement in Europe since WWII, with Poland hosting around 994,000 temporary protection beneficiaries by July 2025, national aggregates did not exhibit a sharp discontinuity. This suggests that the short-term impacts were spatially diffuse and partly absorbed by the rapid access measures. This underscores the need to target services and communication to local settings with a higher arrival concentration.

This work contributes to a reproducible counterfactual forecasting pipeline for non-stationary univariate series anchored at a known intervention. The method trains a stacked LSTM only on pre-intervention data, uses a temporally ordered train/validation/test split consistent with interrupted time series guidance, and forms the post-intervention counterfactual via one-step-ahead forecasts. Repeated fits summarize neural optimization variability, and deviations are reported as explicit absolute and relative effects over a fixed 30-day horizon.

Applied to Poland's COVID-19 time series, the pipeline achieves low validation error and coherent post-intervention tracking. It is an efficient tool for crisis-aware nowcasting with transparent effect quantification.

Contributions of authors: conceptualization, **Dmytro Chumachenko**; methodology, **Mykola Butkevych**, **Dmytro Chumachenko**; software, **Mykola Butkevych**, **Ievgen Meniailov**; validation, **Mykola Butkevych**, **Ievgen Meniailiv**, **Yaroslav Lutsiv**, **Bohdan Kraivskyi**, **Dmytro Chumachenko**; formal analysis, **Mykola Butkevych**, **Dmytro Chumachenko**; investigation, **Mykola Butkevych**, **Ievgen Meniailov**, **Dmytro Chumachenko**; resources, **Dmytro Chumachenko**; data curation, **Mykola Butkevych**; writing-original draft preparation, **Mykola Butkevych**, **Dmytro Chumachenko**; writing-review and editing, **Ievgen Meniailov**, **Yaroslav Lutsiv**, **Bohdan Kraivskyi**; visualization, **Mykola Butkevych**; supervision, **Dmytro Chumachenko**; project administration, **Ievgen Meniailov**, **Dmytro Chumachenko**; funding acquisition, **Dmytro Chumachenko**.

Conflict of interest

The authors declare that they have no conflict of interest concerning this research, whether financial, personal, authorship, or otherwise, that could affect the research and its results presented in this paper.

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Use of Artificial Intelligence

Generative AI tools (Grammarly, ChatGPT 5instant) have been used for grammar checks and text polishing.

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ПЕРЕМІЩЕННЯ НАСЕЛЕННЯ, ЗУМОВЛЕНЕ ВІЙНОЮ, ТА COVID-19 У ПОЛЬЩІ: МОДЕЛЮВАННЯ ІЗ ЗАСТОСУВАННЯМ МОДЕЛІ LSTM

М. В. Буткевич, Є. С. Меняйлов, Я. С. Луців, Б. Б. Краївський, Д. І. Чумаченко

Повномасштабне вторгнення росії в Україну спричинило найбільше й найшвидше переміщення населення в Європі від часів Другої світової війни. Найбільші потоки прийняла Польща. Швидке переміщення

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може впливати на поширення COVID-19 і створювати навантаження на системи тестування, звітності та вакцинації. **Мета:** перевірити, чи пов'язані потоки населення з короткостроковими відхиленнями національної захворюваності на COVID-19 у Польщі від контрфактичної траєкторії, побудованої на довоєнних трендах. **Предмет дослідження:** національні щоденні дані Польщі щодо випадків COVID-19 і смертей. Дані отримано з дашбордів ВООЗ. Охоплення починається з травня 2020 року та зосереджується на подіях 24 лютого 2022 року з горизонтом у 30 днів після вторгнення. **Методи:** було підібрано одновимірну стековану LSTM на довоєнних даних і виконано покрокове (на один крок уперед) прогнозування для перших 30 днів після 24 лютого 2022 року. Архітектура мережі: LSTM(128) - LSTM(64) - Dense(25) - Dense(1) із лінійним виходом. Шкала часу поділена на навчання (до 24 січня 2022 року), валідацію (24 січня - 23 лютого 2022 року) та тестування (24 лютого - +30 днів). Кожен ряд (випадки, смерті) навчено шість разів із різними випадковими ініціалізаціями. Точність оцінена за середньою абсолютною відносною похибкою (MAPE). Відхилення від контрфактичної траєкторії обцінено як абсолютні та відносні показники за 30-денний період. **Результати:** спостережувані щоденні значення відповідали контрфактичній траєкторії протягом першого місяця після вторгнення, із лише помірним, короткочасним переоцінюванням у середині вікна. Середній MAPE зріс із 5,94% до 14,39% для випадків і з 5,90% до 14,62% для смертей між періодами валідації та тестування, що відображає більшу короткострокову невизначеність, але без виразного зламу на національному рівні. **Висновок:** у перший місяць після 24 лютого 2022 року національні часові ряди COVID-19 у Польщі не демонстрували помітного відхилення від контрфактичної траєкторії, попри безпрецедентний міграційний тиск. **Наукова новизна:** дослідження, наскільки нам відомо, є першою зосередженою на Польщі короткостроковою контрфактичною оцінкою шоку від вторгнення, побудованою на даних в умовах реального домінування Omicron. Застосовано просту й прозору LSTM, навчену лише на довоєнних національних даних. Виконано кілька незалежних прогонів для врахування варіабельності навчання. Відхилення кількісно оцінено за чіткими абсолютними та відносними показниками.

Ключові слова: епідемічна модель; епідемічний процес; моделювання епідемії; моделювання; глибоке навчання; LSTM; війна.

Буткевич Микола Віталійович – асп. каф. математичного моделювання та штучного інтелекту, Національний аерокосмічний університет «Харківський авіаційний інститут», Харків, Україна.

Меняйлов Євген Сергійович – канд. техн. наук, доц., в.о. декана факультету математики та інформатики, Харківський національний університет ім. В. Н. Каразіна, Харків, Україна.

Луців Ярослав Степанович – асп. каф. управління проєктами в міському господарстві та будівництві, Харківський національний університет міського господарства імені О. М. Бекетова, Харків, Україна.

Краївський Богдан Богданович – асп., ас. каф. управління проєктами в міському господарстві та будівництві, Харківський національний університет міського господарства імені О. М. Бекетова, Харків, Україна.

Чумаченко Дмитро Ігорович – канд. техн. наук, доц., доц. каф. математичного моделювання та штучного інтелекту, Національний аерокосмічний університет «Харківський авіаційний інститут», Харків, Україна; запрошений дослідник, департамент цифрової та обчислювальної демографії, Інститут демографічних досліджень Макса Планка, Росток, Німеччина.

Mykola Butkevych – PhD Student at the Department of Mathematical Modelling and Artificial Intelligence, National Aerospace University "Kharkiv Aviation Institute", Kharkiv, Ukraine,
e-mail: m.v.butkevych@khai.edu, ORCID: 0000-0001-8189-631X.

Ievgen Meniailov – PhD in Mathematical Modelling and Optimization Methods, Associate Professor, Acting Dean of Mathematics and Informatics Faculty, V. N. Karazin Kharkiv National University, Kharkiv, Ukraine.,
e-mail: evgenii.menyailov@gmail.com, ORCID: 0000-0002-9440-8378.

Yaroslav Lutsiv – PhD Student, Project Management in Urban Management and Construction Department, O. M. Beketov National University of Urban Economy in Kharkiv, Kharkiv, Ukraine,
e-mail: yaroslav.lutsiv@kname.edu.ua, ORCID: 0009-0009-9764-2256.

Bohdan Kraivskyi – PhD Student, Assistant at the Project Management in Urban Management and Construction Department, O. M. Beketov National University of Urban Economy in Kharkiv, Kharkiv, Ukraine,
e-mail: bogdankraivskiy@gmail.com, ORCID: 0000-0002-6700-9240.

Dmytro Chumachenko – PhD, Associate Professor, Associate Professor at the Department of Mathematical Modelling and Artificial Intelligence, National Aerospace University "Kharkiv Aviation Institute", Kharkiv, Ukraine; Visiting Researcher, Department of Digital and Computational Demography, Max Planck Institute for Demographic Research, Rostock, Germany,
e-mail: dichumachenko@gmail.com, ORCID: 0000- 0003-2623-3294.