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Investigating the first wave of the COVID-19 pandemic in Ukraine using epidemiological and genomic sequencing data — Source link \square

Yuriy Gankin, Alina Nemira, Vladimir Koniukhovskii, Gerardo Chowell ...+3 more authors Institutions: Georgia State University, EPAM Systems, University of South Florida Published on: 08 Mar 2021 - medRxiv (Cold Spring Harbor Laboratory Press) Topics: Pandemic and Viral phylodynamics

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Investigating the first stage of the COVID-19 pandemic in Ukraine using epidemiological and genomic data

Yuriy Gankin^{a,*}, Alina Nemira^{b,*}, Vladimir Koniukhovskii^{c,*}, Gerardo Chowell^d, Thomas A. Weppelmann^e, Pavel Skums^{b,**}, Alexander Kirpich^{d,**}

^aQuantori, Cambridge, Massachusetts, United States of America

^bDepartment of Computer Science, Georgia State University, Atlanta, Georgia, United States of America

^cEPAM Systems, Saint Petersburg, Russian Federation ^dDepartment of Population Health Sciences, School of Public Health, Georgia State University, Atlanta, Georgia, United States of America ^eDepartment of Internal Medicine, University of South Florida, Tampa, Florida, United States

Abstract

The novel coronavirus SARS-CoV-2 was first detected in China in December 2019 and has rapidly spread around the globe. The World Health Organization declared COVID-19 a pandemic in March 2020 just three months after the introduction of the virus. Individual nations have implemented and enforced a variety of social distancing interventions to slow the virus spread, that had different degrees of success. Understanding the role of non-pharmaceutical interventions (NPIs) on COVID-19 transmission in different settings is highly important. While most such studies have focused on China, neighboring Asian counties, Western Europe, and North America, there is a scarcity of studies for Eastern Europe. The aim of this study is to contribute to filling this gap by analyzing the characteristics of the *first months of the epidemic* in Ukraine using agent-based modelling and phylodynamics. Specifically, first we studied the dynamics of COVID-19 incidence and mortality and explored the impact of epidemic NPIs. Our stochastic model suggests, that even a small delay of weeks could have increased the number

**Equal Contribution

Corresponding Author: Alexander Kirpich

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^{*}Equal Contribution

Email address: akirpich@gsu.edu (Alexander Kirpich)

of cases by up to 50%, with the potential to overwhelm hospital systems. Second, the genomic data analysis suggests that there have been multiple introductions of SARS-CoV-2 into Ukraine during the early stages of the epidemic. Our findings support the conclusion that the implemented travel restrictions may have had limited impact on the epidemic spread. Third, the basic reproduction number for the epidemic that has been estimated independently from case counts data and from genomic data suggest sustained intra-country transmissions.

Keywords: SARS-CoV-2, agent-based, COVID-19, Ukraine, phylogenetics, phylodynamics

1 1. Introduction

SARS-CoV-2 virus causing COVID-19 was first detected in December 2 2019 in the Chinese city of Wuhan [1][2][3][4][5], and has rapidly spread around the globe, prompting the World Health Organization (WHO) to de-4 clare a pandemic in March, 2020 [6], just three month after the first reported case. Despite having much lower case-fatality rate than other recent coronavirus pandemics such as the severe acute respiratory syndrome (SARS) and Middle East respiratory syndrome (MERS), the novel coronavirus has 8 claimed more lives just within a few months of introduction than both of 9 those epidemics combined [7]. As of June 29, 2021 there were more than 182 10 million infections with over 3.9 million deaths [8]. In the absence of vaccines 11 during the early pandemic period, non-pharmaceutical interventions (specif-12 ically, non-pharmaceutical epidemic mitigation interventions) were the only 13 tools at the disposal of public health authorities to prevent and to mitigate 14 the virus spread [9][10][11]. The strategies implemented and enforced by 15 governments around the world were highly variable and included frequent 16 sanitation of public spaces, enforced social distancing, wearing of masks, clo-17 sure of schools, churches, and ban of mass gatherings [12][13][14]. 18

Even well after a year since the epidemic started, fundamental questions regarding the effects of non-pharmaceutical interventions (NPIs) [15][16] and the genomic evolution of SARS-CoV-2 [17][18][19][20] during the introductory period remain. Additionally, recent modeling efforts aimed at shedding light on those questions have mostly focused on China [1][2][3][4], the rest of Asia [21][22][23], Western and Central Europe [24][22][25], and North America [26][27][28][29][5], largely neglecting Africa, the Middle East, and Eastern

26 Europe.

In Eastern Europe, post-socialist economics and healthcare systems are 27 inherently different from Western Europe. The available SARS-CoV-2 trans-28 mission models for Eastern Europe are based on relatively simple SIR or 29 similar compartmental models [30][31][32] where individuals are assigned to 30 groups and all individuals within a given group are expected to have the 31 same characteristics. To the best of our knowledge no agent-based modeling 32 studies have been conducted for Ukraine to evaluate the impact of spatial 33 heterogeneities in key transmission drivers such as density of infected indi-34 viduals and their geographic locations. Furthermore, the number of genomic 35 epidemiology studies on the COVID-19 pandemic in Eastern Europe has been 36 limited. In this paper, we sought to fill the knowledge gap for the Ukrainian 37 epidemic [33], which provides a unique setting for studying the COVID-19 38 spread under the ex-USSR healthcare system, and with the epidemic miti-30 gation policies similar to the rest of Europe. 40

The first confirmed case in Ukraine was reported on March 3, 2020 and 41 was an individual who has recently traveled from Italy. The first death was 42 reported on March 13, 2020 [34][33]. The Ukrainian government started to 43 implement quarantine measure on March 12, 2020 [33][32] while the cases 44 continued to rise possibly because of the delayed detections of existing infec-45 tions and returns of infected Ukrainians from abroad [32] (Figure 3B). As a 46 result, more strict measures have been implemented on April 6, 2020 which 47 included the closure of schools, universities, shopping malls, and mandatory 48 mask regiment in public places [32]. Those measures were slightly softened 40 on April 24, 2020 and many services resumed even though some restrictions 50 lasted till the end of June 2020 [33]. As a summary, Ukrainian officials took 51 the epidemic very seriously from the beginning and started to implement the 52 mitigation efforts and corresponding regulations almost immediately after 53 multiple cases in the country have been detected. At the same time imple-54 mentation of the proposed mitigation efforts did vary from region to region, 55 and so did the compliance with those regulations [35][36]. 56

57 2. Methods

58 2.1. Agent-based Stochastic Model

To investigate the COVID-19 epidemic in Ukraine and to assess its dynamics under different mitigation scenarios, we utilized our general stochastic agent-based modeling framework [37]. The model was adjusted to the

⁶² Ukrainian settings and fit into the observed Ukrainian data. The summary
⁶³ of the framework together with the adaptation details are outlined below.

In brief, the model simulates the epidemics evolving over the discrete 64 time interval (1, ..., T) with time points $1 \le t \le T$ corresponding to calendar 65 days and over the certain geographical area projected on a plain. Infected 66 individuals are represented as agents with multiple characteristics that in-67 clude geographic coordinates; age; infection time, severity and current sta-68 tus; disease stage; infectivity rate and infectivity radius which determines 69 how frequently and where it produces secondary infections. The summaries 70 of empirical reproduction numbers of individual agents which are generated 71 by model simulations are used for the estimation of the population basic 72 reproduction number \mathcal{R}_0 [38]. The geographical part of the model includes 73 circular local epidemic spread areas $\boldsymbol{E} = \{E_1, E_2, \dots, E_{\mathcal{I}}\}$ characterized by 74 their centers and radii. The centers of these areas represent hostspots of the 75 infection introduction into the local population (e.g. transport hubs or ad-76 ministrative centers). The model incorporates NPI measures via a reduced 77 infection transmission parameters which are effective starting from a certain 78 calendar date customizable within the model. 79

In this study, we used epidemic spread areas and the corresponding in-80 cidence and mortality data reported by the National Security and Defence 81 Council of Ukraine [39]. It includes daily reports for individual administra-82 tive regions ("oblast") under the control of the Ukrainian government start-83 ing from March, 2020. The reported data was separated into three parts. 84 The initially reported cases from March 12, 2020 to April 12, 2020 were ret-85 rospectively incorporated into the model as the initial conditions [37]. The 86 reported and model-produced data from April 22, 2020 to July 12, 2020 were 87 used for model calibration, and from July 13, 2020 to August 1, 2020 - for88 model validation. The data before April 22, 2020 were used solely for the 89 initial conditions to increase the model fit robustness, since the initial num-90 ber of cases was relatively small in comparison to subsequent periods. The 91 August 1, 2020 has been selected as the end date of our simulations to agree 92 with the dates of genomic analysis based on available analyzed SARS-CoV-2 93 sequences collection times [40]. 94

Optimization of model parameters has been performed by minimizing the sum of squared differences between the model-produced outputs (across multiple runs) and the calibration data using the Nelder-Mead numerical minimization method [41]. The population basic reproduction number \mathcal{R}_0 [38] has been estimated from the model-produced distribution quantiles (5%,

median, 95%) of the reproduction numbers of individuals and summarized across multiple stochastic runs [37]. The estimates for \mathcal{R}_0 were produced from the model fit to real data with the assumption that interventions have started almost immediately after the virus introduction.

In addition to the simulations based on the model fit to the actual case count, mortality and NPI data, two alternative simulation scenarios were considered under the hypothetical assumptions that NPIs that caused reduced transmissibility were implemented one (on April 19, 2020) and two (on April 26, 2020) weeks after the simulation start time. The results of simulations under these three scenarios were compared to assess the effect of timely NPI implementations.

The additional details about the model can be found in our earlier study [37], and the model implementation tailored to Ukrainian data is available at https://github.com/quantori/COVID19-Ukraine-Transmission.

114 2.2. Genomic Epidemiology Analysis

Sixty high-quality SARS-CoV-2 genomes from Ukraine sampled between 115 April 24, 2020 and August 7, 2020 were extracted from GISAID [40]. These 116 genomes were utilized to construct a maximum likelihood phylogeny using 117 Nextstrain build for SARS-CoV-2 with the default country-specific subsam-118 pling settings [42]. The obtained timed phylogeny contained Ukrainian se-119 quences together with a representative subsample of 6479 sequences from 120 other geographic regions, and included inferred ancestral geographic traits of 121 internal nodes. Using these traits, intra-country transmission clusters were 122 identified as clades with the most recent common ancestors (MRCA) esti-123 mated as originating from Ukraine. For each cluster, confidence intervals for 124 emergence times for MRCA and its parent were also obtained. 125

Next, a phylodynamic analysis of the three largest clusters and the en-126 tire Ukrainian SARS-CoV-2 population was performed using BEAST v1.10.4 127 [43]. We used a strict molecular clock, $HKY+\Gamma$ nucleotide substitution 128 model, a tree prior with exponential growth coalescent. Priors for the pa-129 rameters were defined in BEAUti v 1.10.4 and were the following: a) nor-130 mal $\mathcal{N}(mean = 8.0e-4, st.dev = 2.0e-5)$ for the clock rate, b) log-normal 131 $\mathcal{LN}(mean = 1.0, st.dev = 1.25)$ for the population size, c) double ex-132 ponential (Laplace) distribution $\mathcal{DEXP}(\mu = 0, b = 100)$ for the growth 133 rate, d) normal $\mathcal{N}(mean = 0, st.dev = 1)$ for the freqParameter, e) ex-134 ponential $\mathcal{EXP}(mean = 0.5, offset = 0)$ for the gammaShape parameter, 135

and f) log-normal $\mathcal{LN}(mean = 1.0, st.dev = 1.25)$ for the kappa param-136 eter. The detailed parameters file is available in XML format at https: 137 //github.com/alanira/COVID19-Ukraine-phylodynamics. The parame-138 ters were estimated after 30,000,000 iterations of Markov Chain Monte Carlo 139 (MCMC) sampling, with the initial 10% values discarded as burn-in. The 140 results were accepted if the effective sample sizes were above 200 for all pa-141 rameters. The estimated exponential growth rates were used to calculate 142 the basic reproduction numbers \mathcal{R}_0 under the assumption that SARS-CoV-2 143 generation intervals (i.e. times between infection onset and onward trans-144 mission) were gamma-distributed [44]. We used the formula 145

$$\hat{\mathcal{R}}_0 = \left[1 + \frac{\hat{f}\hat{\sigma}^2}{\hat{\mu}}\right]^{\frac{\hat{\mu}^2}{\hat{\sigma}^2}},\tag{1}$$

where $\hat{\mu}$ and $\hat{\sigma}$ are the mean and standard deviation of the aforementioned gamma distribution [45][46][47][48]. For these values, we used the estimates $\hat{\mu} = 5.20$ and $\hat{\sigma} = 1.72$ from [49] and $\hat{\mu} = 3.95$ and $\hat{\sigma} = 1.51$ from [49]. The formula (1) defines a strictly monotone transformation of \hat{f} , and, therefore, it also straightforwardly transforms the 95% highest posterior density (HPD) intervals for f into those for \mathcal{R}_0 .

152 3. Results

153 3.1. Agent-based Stochastic Model

The visual results of the first scenario (model fit) and the corresponding outputs are summarized in Figure 1. Blue curves in Figure 1 correspond to the reported data. They are captured by the model fits which is also indicated by the corresponding median and 90% pointwise model prediction bands across five hundred runs. The calibration interval is highlighted by cyan background.

For each of the three considered scenarios the median value across five hundred simulations were computed at each time point and presented together with the corresponding 5-th and 95-th percentiles across five hundred stochastic realizations to form the 90% prediction intervals (PI-s). The corresponding results are summarized in Tables 1 and 2 for the model-predicted cases and deaths, respectively. The three scenario summaries from Table 1 can be directly compared. For comparison the actual number of reported



Figure 1: The model predictions together with the reported cases (Panel A) and reported death (Panel B) are presented. The model calibration time interval is highlighted in green. Red lines correspond to the median of the five hundred model-produced runs together with the corresponding 90% prediction bands to quantify the uncertainty. The actual observed case and death counts are displayed in blue for visual comparison.

cases by August 1, 2020 was 71,056 [39] which validates the model fit since 167 August 1, 2020 was outside of the calibration interval. The hypothetical 168 April 19th and April 26th intervention start dates produce larger number of 169 cases in comparison to the original fitted scenario. The median estimates 170 can be compared directly. The hypothetical April 19th scenario results in 171 16% predicted increase in cumulative number of cases on June 1, 2020 and 172 in 20% predicted increase in cumulative number of cases on August 1, 2020 173 in comparison to the fitted scenario. The hypothetical April 26th scenario 174 results in 36% predicted increase in cumulative number of cases on June 1, 175 2020 and in 46% predicted increase in cumulative number of cases on August 176 1, 2020 when compared to the fitted scenario. 177

The hypothetical April 19th scenario results in 14% increase in cumulative number of deaths predicted on June 1, 2020 and in 20% increase in cumulative number of deaths predicted on August 1, 2020. The hypothetical April 26th scenario results in 32% increase in cumulative number of deaths predicted on June 1, 2020 and in 46% increase in cumulative number of deaths predicted on August 1, 2020.

Interestingly, the median results for the hypothetical April 19th scenario displayed better alignment with the actual data. This suggests the delayed impact of NPIs in transmission mitigation caused by the time needed to put the prescribed measures into effect. Furthermore, the obtained results demonstrate the importance of the early epidemic mitigation measures which cause the reduction in transmission probability parameters and, therefore, a

Scenario	June 1,2020	July 1,2020	August 1,2020
Real Data	24,012	44,998	71,056
April 12, 2020	23,724 (19,093;28,250)	38,932 (29,181;48,782)	57,810 (41,864;75,029)
April 19, 2020	27,511 (22,681;32,872)	46,193 (36,238;57,100)	$69,358\ (50,642;88,407)$
April 26, 2020	32,220 (26,016;38,645)	$55,141 \ (41,974;69,992)$	84,227 (63,992;109,069)

Table 1: The model outputs are presented together with the reported data. The predicted number of cumulative cases produced by the model over time for three different epidemic mitigation scenarios for three initiation dates together with the corresponding 90% prediction intervals.

Scenario	June 1,2020	July 1,2020	August 1,2020
Real Data	718	1,173	1,709
April 12, 2020	568(464;667)	$967\ (738; 1, 203)$	$1,461 \ (1,050;1,904)$
April 19, 2020	653 (541;783)	$1,143 \ (889;1,412)$	1,762(1,308;2,241)
April 26, 2020	$752 \ (612; 906)$	$1,364 \ (1,049;1,705)$	$2,141 \ (1,604;2,719)$

Table 2: The model outputs are presented together with the reported data. The predicted number of cumulative death produced by the model over time for three different epidemic mitigation scenarios for three initiation dates together with the corresponding 90% prediction intervals.

reduction in the number of cases, and (more importantly) deaths. At the 190 same time the results for later mitigation efforts implementation dates should 191 only be interpreted as sensitivity analysis, since the Ukrainian government 192 has implemented quarantine measures from the beginning of the epidemic and 193 there were no data to properly estimate the corresponding non-intervention 194 transmission probability parameters [50]. Therefore, the corresponding non-195 quarantine probability parameters have been adopted from the previous anal-196 ysis [37]. 197

The population basic reproduction number \mathcal{R}_0 estimate during the intervention was estimated to be 1.10 (median) with the corresponding 90% confidence interval from quantiles equal to (0.24; 1.88).

201 3.2. Genomic epidemiology of SARS-CoV-2

Despite a sparse sampling, the observed genomic diversity of SARS-CoV-2 in Ukraine is substantial, indicating both multiple introductions of the virus and sustained intra-country evolution (Figure 2). This agrees well with the patterns observed in other countries [51], and emphasizes the contribution of global movement of people to the rapid spread of SARS-CoV-2. Specifically,

²⁰⁷ Ukrainian sequences are distributed among eight lineages by the classification ²⁰⁸ of [52] as follows: B.1 - 50.0 % of genomes, B.1.1 - 28.3 %, B1.1.243 - 8.3 %, ²⁰⁹ B.1.527 - 5.0 %, B.1.1.325 - 3.3 %, and 1.7 % for each B.1.131, B.1.1.194, ²¹⁰ B. Similarly, by Nextstrain classification the distribution of lineages is: 19A ²¹¹ - 1.7 %, 20A - 51.7 % and 20B - 46.7 % (Figure 2).



Figure 2: The global phylogenetic tree of SARS-CoV-2 genomes: A) distribution of Ukrainian SARS-CoV-2 genomes inside global SARS-CoV-2 population, B) the same tree with global SARS-CoV-2 lineages highlighted.

Seven Ukrainian clusters contain multiple sequences and jointly constitute 73.3% of all sampled genomes. Presence of these clusters and the corresponding intra-country lineages indicate sustained internal transmissions (Figure 3A and Figure A1-A7 in Appendix). For each such lineage, a confidence interval of its introduction time can be assessed by the union of the confidence intervals for inferred dates of its Ukrainian MRCA v and the non-Ukrainian parent of v (Table A2 in Appendix).

We analyzed these introduction times relatively to the implementation 219 time of the travel ban, that was established on March 16, 2020 [53] for foreign 220 citizens and on March 17, 2020 [54] for all travelers with the exception of 221 Ukrainian citizens returning from abroad. It turned out that three out of 222 seven lineages were most likely introduced into the country after the travel 223 ban date, as indicated by their introduction confidence intervals (Figure 4). 224 Similarly, a single lineage was likely imported before that date; for three 225 remaining lineages the travel ban date falls into their confidence intervals, 226

preventing us from the decisive conclusion, even though the date lies closer to the left ends of all intervals. Thus, the analysis support the hypothesis that the travel restrictions had limited effect on the virus importation control.

The estimates of the basic reproduction number \mathcal{R}_0 for three largest lineages are summarized in Table 3. All estimates are significantly above one, indicating sustained local transmission of SARS-CoV-2 during the first months of the epidemic in Ukraine.

Cluster	$\hat{\mu}$	$\hat{\sigma}$	$\hat{\mathcal{R}}_0$ & 95% CI	$\hat{oldsymbol{\mu}}$	$\hat{\sigma}$	$\hat{\mathcal{R}}_0$ & 95% CI
First	5.20	1.72	$1.31 \ (1.12; \ 1.52)$	3.95	1.51	$1.23 \ (1.09; \ 1.37)$
Second	5.20	1.72	$1.47 \ (1.1; \ 1.98)$	3.95	1.51	$1.34 \ (1.07; \ 1.68)$
Third	5.20	1.72	1.48 (1.16; 1.94)	3.95	1.51	$1.35\ (1.12;\ 1.65)$

Table 3: The estimates of the basic reproduction number \mathcal{R}_0 for three largest clusters together with the corresponding 95% confidence intervals (CI-s). The results are reported for two pairs of generation interval distribution parameters $\hat{\mu}$ and $\hat{\sigma}$ reported by two studies

234 4. Discussion

In this study, we have detailed the epidemic characteristics of the first 235 months of the COVID-19 pandemic in Ukraine and studied the effects of 236 NPIs. We considered two complementary approaches based on the stochas-237 tic modeling applied to incidence data and genomic epidemiology methods 238 applied to sequencing data. Different types of data reflect various aspects 230 of the epidemics, and are prone to different biases. Therefore, such syn-240 thetic approach facilitates ubiquitous understanding of the early stages of 241 the epidemic in Ukraine. 242

COVID-19 pandemic is characterized by a richness of available data, that 243 allow to utilize agent-based modelling and genomic analysis at the finest pos-244 sible resolution. In Ukraine, we have an access to public health data on the 245 level of individual regions, which makes agent-based model predictions more 246 comprehensive. Similarly, the advances and cost reduction of next-generation 247 sequencing (NGS) methods allowed rapid genomic data acquisition at early 248 stages of the epidemic [40]. These data processed by advanced phyloge-249 netic and phylodynamic models allow to assess the virus importation and 250 intra-country transmission dynamics from a "different angle" [55]. Further-251 more, in cases when two methods produced independent estimations of the 252 basic reproduction number \mathcal{R}_0 , the obtained results are comparable, thus 253



Figure 3: Panel A: The SARS-CoV-2 clusters are presented in the Ukrainian phylogenetic tree. Clusters colored by blue, red, green, pink, orange, azure, yellow, and numbered from one to seven, respectively. Panel B: Daily incidence of reported cases for Ukraine (orange) together with the sample counts and collection dates for sequenced samples (black). The travel restriction has happened on March 17, 2020, which is indicated by a vertical dark red bar time separator in both panels.



TMRCA Uncertainty Summaries For Detected Clusters

Figure 4: Introduction times for seven largest Ukrainian transmission lineages visualized from Table A2 from the supplement. The estimated intervals for introduction times are depicted as horizontal lines, the border closure date (March 17, 2020) is indicated by a vertical line.

highlighting their consistency. The uncertainty estimates for the stochastic
estimates are wider, which may be due to the fact that stochastic model has
more parameters and higher variability in the outputs while phylodynamic
models has pretty strong priors.

The study has limitations since the available surveillance incidence and 258 genomic molecular data are limited. Ukraine is one of the poorest countries 259 in Europe (based on GDP per capita), and, therefore, the health care infras-260 tructure in Ukraine lacks in some parts the resources of its close and distant 261 European neighbors [56]. As a result, both availability of screening tests and 262 the reporting of incidence data during the initial epidemic likely (substan-263 tially) underestimated the burden of disease in terms of incidence counts. 264 Likewise, as the pandemic evolved, the scarcity of genetic sequencing limited 265 the number of sequence comparison in the phylogenetic analysis. As such, the 266 actual number of viral clusters of local transmission remains unknown and 267 should be interpreted as at least seven clusters which only form the "tip of the 268 iceberg" of all transmission clusters. Moreover, the local population compli-269 ance with the NPI regulations implemented by officials is always a question, 270 which might have reduced the effectiveness of such measures [35][36]. 271

In summary, this study was among the first to explore the characteris-

tics of the initial pandemic as it spread to Ukraine *and* provided additional *genomic analysis* not previously published.

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284 References

- [1] N. Zhu, D. Zhang, W. Wang, X. Li, B. Yang, J. Song, X. Zhao, B. Huang,
 W. Shi, R. Lu, et al., A novel coronavirus from patients with pneumonia
 in china, 2019, New England Journal of Medicine (2020).
- [2] H. Lu, C. W. Stratton, Y.-W. Tang, Outbreak of pneumonia of un known etiology in wuhan china: the mystery and the miracle, Journal
 of Medical Virology (2020).
- [3] C. Huang, Y. Wang, X. Li, L. Ren, J. Zhao, Y. Hu, L. Zhang, G. Fan,
 J. Xu, X. Gu, et al., Clinical features of patients infected with 2019 novel coronavirus in wuhan, china, The lancet 395 (2020) 497–506.
- [4] N. Chen, M. Zhou, X. Dong, J. Qu, F. Gong, Y. Han, Y. Qiu, J. Wang,
 Y. Liu, Y. Wei, et al., Epidemiological and clinical characteristics of 99 cases of 2019 novel coronavirus pneumonia in wuhan, china: a descriptive study, The Lancet 395 (2020) 507–513.
- [5] M. Ciotti, M. Ciccozzi, A. Terrinoni, W.-C. Jiang, C.-B. Wang,
 S. Bernardini, The covid-19 pandemic, Critical Reviews in Clinical
 Laboratory Sciences 57 (2020) 365–388.
- [6] WHO, https://www.who.int/dg/speeches/detail/who-directorgeneral-s-opening-remarks-at-the-media-briefing-on-COVID 19---11-march-2020, 2020. Accessed: 2021-02-20.
- [7] E. Mahase, Coronavirus: covid-19 has killed more people than sars and mers combined, despite lower case fatality rate, BMJ (2020).
- [8] Johns Hopkins University Coronavirus Resource Center, https://
 coronavirus.jhu.edu/map.html, 2021. Accessed: 2021-03-01.
- W.-H. Chen, U. Strych, P. J. Hotez, M. E. Bottazzi, The SARS-CoV-2
 vaccine pipeline: an overview, Current tropical medicine reports (2020)
 1-4.
- [10] S. Caddy, Russian SARS-CoV-2 vaccine, BMJ: British Medical Journal
 (Online) 370 (2020).

- [11] A. Mullard, How COVID vaccines are being divvied up around the
 world, Nature (2020). URL: https://doi.org/10.1038/d41586-020 03370-6. doi:10.1038/d41586-020-03370-6.
- [12] N. Islam, S. J. Sharp, G. Chowell, S. Shabnam, I. Kawachi, B. Lacey,
 J. M. Massaro, R. B. D'Agostino, M. White, Physical distancing interventions and incidence of coronavirus disease 2019: natural experiment
 in 149 countries, bmj 370 (2020).
- 13] WHO, https://www.who.int/emergencies/diseases/novelcoronavirus-2019/advice-for-public, 2020. Accessed: 2021-02-20.
- [14] CDC, https://www.cdc.gov/coronavirus/2019-ncov/prevent getting-sick/social-distancing.html, 2020. Accessed: 2021-02-20.
- ³²⁴ [15] F. Di Gennaro, D. Pizzol, C. Marotta, M. Antunes, V. Racalbuto,
 N. Veronese, L. Smith, Coronavirus diseases (covid-19) current sta³²⁶ tus and future perspectives: a narrative review, International journal of
 ³²⁷ environmental research and public health 17 (2020) 2690.
- [16] K. Iyengar, A. Mabrouk, V. K. Jain, A. Venkatesan, R. Vaishya, Learning opportunities from covid-19 and future effects on health care system, Diabetes & Metabolic Syndrome: Clinical Research & Reviews 14 (2020) 943–946.
- [17] K. Tizaoui, I. Zidi, K. H. Lee, R. Abou Ghayda, S. H. Hong, H. Li,
 L. Smith, A. Koyanagi, L. Jacob, A. Kronbichler, et al., Update of
 the current knowledge on genetics, evolution, immunopathogenesis, and
 transmission for coronavirus disease 19 (covid-19), International Journal
 of Biological Sciences 16 (2020) 2906.
- [18] H. Yi, 2019 novel coronavirus is undergoing active recombination, Clin ical Infectious Diseases (2020).
- [19] C. Li, Y. Yang, L. Ren, Genetic evolution analysis of 2019 novel coronavirus and coronavirus from other species, Infection, Genetics and Evolution (2020) 104285.
- [20] D. Benvenuto, M. Giovanetti, A. Ciccozzi, S. Spoto, S. Angeletti, M. Ciccozzi, The 2019-new coronavirus epidemic: evidence for virus evolution,
 Journal of medical virology 92 (2020) 455-459.

- ³⁴⁵ [21] W. E. Wei, Z. Li, C. J. Chiew, S. E. Yong, M. P. Toh, V. J. Lee,
 Presymptomatic transmission of SARS-CoV-2—singapore, january 23–
 march 16, 2020, Morbidity and Mortality Weekly Report 69 (2020) 411.
- ³⁴⁸ [22] N. Yamamoto, G. Bauer, Apparent difference in fatalities between central europe and east asia due to SARS-CoV-2 and covid-19: Four hypotheses for possible explanation, Medical Hypotheses (2020) 110160.
- [23] D. Roy, S. Tripathy, S. K. Kar, N. Sharma, S. K. Verma, V. Kaushal,
 Study of knowledge, attitude, anxiety & perceived mental healthcare
 need in indian population during covid-19 pandemic, Asian Journal of
 Psychiatry (2020) 102083.
- ³⁵⁵ [24] H. Salje, C. T. Kiem, N. Lefrancq, N. Courtejoie, P. Bosetti, J. Paireau,
 ³⁵⁶ A. Andronico, N. Hozé, J. Richet, C.-L. Dubost, et al., Estimating the
 ³⁵⁷ burden of SARS-CoV-2 in france, Science (2020).
- [25] A. Fokas, N. Dikaios, G. Kastis, Mathematical models and deep learning
 for predicting the number of individuals reported to be infected with
 SARS-CoV-2, Journal of the Royal Society Interface 17 (2020) 20200494.
- [26] I. Ghinai, T. D. McPherson, J. C. Hunter, H. L. Kirking, D. Christiansen, K. Joshi, R. Rubin, S. Morales-Estrada, S. R. Black, M. Pacilli, et al., First known person-to-person transmission of severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) in the usa, The Lancet (2020).
- [27] S. Ellington, P. Strid, V. T. Tong, K. Woodworth, R. R. Galang, L. D.
 Zambrano, J. Nahabedian, K. Anderson, S. M. Gilboa, Characteristics
 of women of reproductive age with laboratory-confirmed SARS-CoV-2
 infection by pregnancy status—united states, january 22–june 7, 2020,
 Morbidity and Mortality Weekly Report 69 (2020) 769.
- [28] J. D. Silverman, N. Hupert, A. D. Washburne, Using influenza surveillance networks to estimate state-specific prevalence of SARS-CoV-2 in
 the united states, Science translational medicine 12 (2020).
- J. R. Fauver, M. E. Petrone, E. B. Hodcroft, K. Shioda, H. Y. Ehrlich,
 A. G. Watts, C. B. Vogels, A. F. Brito, T. Alpert, A. Muyombwe, et al.,
 Coast-to-coast spread of SARS-CoV-2 during the early epidemic in the
 united states, Cell (2020).

- [30] A. Issanov, Y. Amanbek, A. Abbay, S. Adambekov, M. Aljofan,
 A. Kashkynbayev, A. Gaipov, Covid-19 outbreak in post-soviet states:
 modeling the best and worst possible scenarios (2020).
- [31] I. Nesteruk, Long-term predictions for covid-19 pandemic dynamics in
 ukraine, austria and italy, Europe PMC (2020).
- [32] Y. N. Kyrychko, K. B. Blyuss, I. Brovchenko, Mathematical modelling of
 the dynamics and containment of covid-19 in ukraine, Scientific reports
 10 (2020) 1–11.
- ³⁸⁶ [33] A. Åslund, Responses to the covid-19 crisis in russia, ukraine, and ³⁸⁷ belarus, Eurasian Geography and Economics (2020) 1–14.

[34] Kyiv Post, https://www.kyivpost.com/ukraine-politics/
 developing-first-coronavirus-case-identified-in ukraine.html, 2020. Accessed: 2021-02-20.

- [35] UN report: Impact of COVID-19 on human rights in Ukraine
 , https://www.ohchr.org/Documents/Countries/UA/Ukraine_COVID 19_HR_impact_EN.pdf, 2020. Accessed: 2021-06-29.
- [36] Atlantic Council: Ukraine's local authorities and the Covid-19
 pandemic, https://www.atlanticcouncil.org/blogs/ukrainealert/
 ukraines-local-authorities-and-the-covid-19-pandemic/, 2021.
 Accessed: 2021-06-29.
- [37] A. Kirpich, V. Koniukhovskii, V. Shvartc, P. Skums, T. A. Weppelmann,
 E. Imyanitov, S. Semyonov, K. Barsukov, Y. Gankin, Development of
 an interactive, agent-based local stochastic model of COVID-19 transmission and evaluation of mitigation strategies illustrated for the state
 of Massachusetts, USA, PLoS ONE 16 (2021) e0247182.
- [38] G. N. Milligan, A. D. Barrett, An Essential Guide, Wiley Online Library,
 2015.
- [39] National Security And Defence Council of Ukraine, bhttps://
 covid19.rnbo.gov.ua/, 2021. Accessed: 2021-02-20.
- [40] GISAID, A global initiative on sharing avian flu data., https://
 www.gisaid.org/, 2020. Accessed: 2021-02-20.

- ⁴⁰⁹ [41] J. A. Nelder, R. Mead, A simplex method for function minimization, ⁴¹⁰ The computer journal 7 (1965) 308–313.
- [42] github.com, https://github.com/nextstrain/ncov, 2021. Accessed:
 2020-11-01.
- [43] M. A. Suchard, P. Lemey, G. Baele, D. L. Ayres, A. J. Drummond,
 A. Rambaut, Bayesian phylogenetic and phylodynamic data integration
 using beast 1.10, Virus evolution 4 (2018) vey016.
- [44] Q. Li, X. Guan, P. Wu, X. Wang, L. Zhou, Y. Tong, R. Ren, K. S.
 Leung, E. H. Lau, J. Y. Wong, et al., Early transmission dynamics in
 wuhan, china, of novel coronavirus-infected pneumonia, New England
 Journal of Medicine (2020).
- [45] BEAST Software, https://beast.community/estimating_R0.html,
 2020. Accessed: 2021-02-20.
- 422[46]BEASTSoftware,https://beast.community/423phylodynamics_of_epidemic_influenza, 2020. Accessed: 2021-02-20.
- [47] J. Wallinga, M. Lipsitch, How generation intervals shape the relationship
 between growth rates and reproductive numbers, Proceedings of the
 Royal Society B: Biological Sciences 274 (2007) 599–604.
- ⁴²⁷ [48] N. C. Grassly, C. Fraser, Mathematical models of infectious disease transmission, Nature Reviews Microbiology 6 (2008) 477–487.
- [49] T. Ganyani, C. Kremer, D. Chen, A. Torneri, C. Faes, J. Wallinga,
 N. Hens, Estimating the generation interval for coronavirus disease
 (covid-19) based on symptom onset data, march 2020, Eurosurveillance
 25 (2020) 2000257.
- 433 [50] github.com, https://github.com/quantori/COVID19-Ukraine 434 Transmission, 2021. Accessed: 2020-11-01.
- I. L. Geoghegan, X. Ren, M. Storey, J. Hadfield, L. Jelley, S. Jefferies,
 J. Sherwood, S. Paine, S. Huang, J. Douglas, et al., Genomic epidemiology reveals transmission patterns and dynamics of SARS-CoV-2 in
 aotearoa new zealand, Nature communications 11 (2020) 1–7.

- [52] A. Rambaut, E. C. Holmes, A. O'Toole, V. Hill, J. T. McCrone, C. Ruis,
 L. du Plessis, O. G. Pybus, A dynamic nomenclature proposal for SARSCoV-2 lineages to assist genomic epidemiology, Nature microbiology 5
 (2020) 1403–1407.
- 443 [53] baltsi.mfa.gov.ua No Entry for Foreigners May 26, 2020 ,
 https://baltsi.mfa.gov.ua/ru/news/timchasova-zaborona-do24-kvitnya-2020-r-na-peretinannya-derzhavnogo-kordonu-navyizd-v-ukrayinu-dlya-inozemciv-ta-osib-bez-gromadyanstva,
 2021. Accessed: 2021-02-20.
- 448 [54] Closed borders, https://www.kmu.gov.ua/news/uryad 449 timchasovo-zaboroniv-vyizd-v-ukrayinu-inozemciv-ta-zakriv 450 mizhnarodne-pasazhirske-aviaspoluchennya, 2021. Accessed:
 451 2021-02-20.
- [55] G. L. Armstrong, D. R. MacCannell, J. Taylor, H. A. Carleton, E. B.
 Neuhaus, R. S. Bradbury, J. E. Posey, M. Gwinn, Pathogen genomics in public health, New England Journal of Medicine 381 (2019) 2569–2580.
- 455 [56] emerging-europe.com, https://emerging-europe.com/news/imf 456 ukraine-is-emerging-europes-poorest-country/, 2021. Accessed:
 457 2021-03-01.