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Evaluating the Impact of the Pandemic for the Low- and Middle-Income Countries Using Multimodal Data

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Abstract. Compared with high-income countries, Low- and Middle-income Countries (LMICs) are characterized by large and dense populations with low standards of living. During major public health events, medical resources are often strained in LMICs. The COVID-19 pandemic has upended health and living standards around the world. This paper analyzes the impact of COVID-19 pandemic on medical resources in LMICs using multimodal data, including static attributes and epidemic time series data of countries. Specifically, we use the dynamic models to predict the maximum hospital demand and number of infections for the LMICs in the COVID-19 pandemic. The epidemic is estimated to impose health care burden excessively exceeding the current capacity of hospitals in many LMICs, especially in Honduras, Central African Republic, and Colombia. The reasons for the shortage of medical resources in these areas are further analyzed. We provide suggestion on coping with the shortage of medical resources in the COVID-19 era, as well as preparations for preventing major public health events in the future.

Keywords: Covid-19; Prediction model; Hospital demand; LMICs; Multimodal.

1. Introduction

The outbreak of the coronavirus disease 2019 (COVID-19) has spread across the world. In the early stage of the COVID-19 epidemic, the lack of awareness of the epidemic, weak prevention and control efforts, and large-scale population movement created favorable conditions for the spread of the COVID-19. The virus mutates many times. For any country or region, the outbreak of COVID-19 not only seriously threatens humans' health, but also does damage to the existing medical system and causes serious economic losses to various industries [1]. The massive increase in infection has overwhelmed the healthcare infrastructure. In response to this major public health emergency, lots of countries and regions have taken a series of comprehensive prevention and intervention measures. These multifaceted interventions have, to some extent, slowed the speed and scope of COVID-19 transmission. However, there are still no specific drugs for the treatment of COVID-19, and the prevention and control of the epidemic still cannot be ignored.

The availability of medical resources is closely related to the number of infections, and we tend to care about the use of medical resources when the number of infections reaches the certain high value, such as the number of beds, the number of ventilators, etc. Research has been conducted on predicting the number of infected and confirmed cases, but there are very few studies on the estimation of medical resources demand and utilization. Although most of the high-income countries have reached the peak of the COVID-19 epidemic [2], the epidemic still spread in most of the low- and middle- income countries (LMICs). Unlike high-income countries, the LMICs are more likely to encounter serious shortage of health care resources.

In the post-epidemic era, the influx of a large number of positive infections into hospitals will inevitably lead to a run on hospital resources, resulting in many people not receiving timely treatment and causing serious social harm. Researchers have found association between mortality and health care resources, emphasizing the importance of effective disease control in resource-limited regions [3]. Our study predicts the maximum hospital demand and number of infections for the LMICs in the COVID-19 pandemic, with the aim of providing specific disease control guidance for the LMICs.

The remainder of this paper is organized as follows. Section 2 outlines the related work in predicting the pandemic, especially for COVID-19. Section 3 describes the framework of the

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proposed model and details its mathematical theory. Section 4 provides the experimental results using the real multimodal data of 58 LMICs, and analyzes the results of different countries. The conclusion is provided in Section 5.

2. Related Work

The mechanistic approaches like compartmental and agent-based models are widely used in predicting the pandemic.

Compartmental mathematical models include the Susceptible-Infectious-Recovery (SIR) model and its derived models, such as SEIR. These models divide the population into exclusive groups, and define the progress among the different groups through ordinary differential equations. Kim S., et al [4] developed a novel SEIR model based on the Coxian distribution approximating the distribution of the incubation. The model is adaptive for resolving the various realistic epidemic prediction since all types of incubation period are approximated by the Coxian distribution.

However, several parameters need to be fitted using the real epidemic data, which is a non-trivial problem. Chen S., et al. [5] proposed a more generalized version of the SIR model, where the infection rate and the removal rate both vary with time. The reciprocal regression is used to estimate the infect rate and the recovery rate curve is fitted using the last five data. The model is evaluated to tracks the epidemic of COVID-19 in 30 provinces in China and 15 cities in Hubei province. Chen Y., et al. [6] also derived a time-dependent SIR model that tracks the transmission and recovering rate at time t. Due to the existence of asymptomatic infections of COVID-19, they extend the model by considering two types of infected persons: detectable and undetectable infected persons. Giordano G., et al [7] proposed the SIDARTHE model considering eight stages of infection. The model discriminated the infected individuals according to whether they have been diagnosed and the severity of their symptoms. The prediction of the model in the long run are not very sensitive to the initial conditions, but they are sensitive to parameters in the model estimated using empirical data.

Few studies focus on the impact of COVID-19 pandemic on medical resources utilization quantitatively. In this paper, we derive the relationship between the number of infections and the utilization of hospital beds based on the infectious disease dynamics model.

3. Methodology

3.1 Number of Infections and Maximum Hospital Demand Estimation

3.1.1 Dynamic Model

Let $S(t)$, $I(t)$ and $R(t)$ be the counts of susceptible, infected and recovered (including dead) people in a given area at time t, respectively. Let N be the population of the city/province.

The Susceptible-Infective-Removal (SIR) model is a commonly used epidemiology model for the dynamic of susceptible $S(t)$, infected $I(t)$ and recovered $R(t)$ as a system of ordinary differential equations [8]. Given that the infectious rate β and the removal rate γ change with respect to time, we obtain the time-varying SIR model [9].

$$\begin{cases} \dfrac{dS}{dt} = -\beta(t)\dfrac{S(t)}{N}I(t) \\ \dfrac{dI}{dt} = \beta(t)\dfrac{S(t)}{N}I(t) - \gamma(t)I(t) \\ \dfrac{dR}{dt} = \gamma(t)I(t) \end{cases}$$

where $\beta(t)$ and $\gamma(t)$ are unknown function of time.

Dividing the first, the second equation by the third equation in above equations, respectively, we obtain

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$$\begin{cases} \dfrac{dC}{dR} = \dfrac{\beta(t)}{\gamma(t)}\dfrac{S(t)}{N} \\ \dfrac{dS}{dR} = -\dfrac{\beta(t)}{\gamma(t)}\dfrac{S(t)}{N} \end{cases}$$

where $dC = dI + dR$.

Since the infectious rate and removal rate are not only associated with time, but also with the cumulative number of recovery (including death), then in a certain period we have

$$\begin{cases} \dfrac{dC}{dR} = \rho(R)\dfrac{S(R)}{N} \\ \dfrac{dS}{dR} = -\rho(R)\dfrac{S(R)}{N} \end{cases}$$

where $\rho(R) = \beta(R)/\gamma(R)$.

In the early stage of the epidemic, $\rho(R)$ was large and fluctuated significantly, and then $\rho(R)$ gradually decreased to 0. Specifically, if $\rho(R) > 1$, the number of hospitalized people is increasing; if $\rho(R) < 1$, the number of hospitalized people is decreasing.

Given that the number of susceptible people is equal to the population of the city/province at $t = 0$, from the second equation in the third equations, we obtain

$$S(R) = N * \exp\{-\frac{1}{N}\int_0^R \rho(\mu)d\mu\}$$

Thus,

$$\frac{dC}{dR} = \rho(R)\exp\{-\frac{1}{N}\int_0^R \rho(\mu)d\mu\}$$

Let $\eta(R) = \rho(r)\exp\{-\frac{1}{N}\int_0^R \rho(\mu)d\mu\}$, then

$$\frac{dC}{dR} = \eta(R)$$

Especially, when the cumulative number of confirmed cases is small compared with the population, we can get $\eta(R) \approx \rho(R)$, then $\frac{dC}{dR} = \rho(R)$.

3.1.2 Estimation and Fitting

We use the linear regression model for p points to obtain the discrete values of $\eta(R)$, that is, $\eta(R_i)$ for $i = 1,2,3\cdots,n$. The detailed steps of method are as follows.

(1) Let $\{(R_1, C_1), (R_2, C_2), \cdots, (R_n, C_n)\}$ be n pairs of samples of (R, C), where $R_1 < R_2 < \cdots < R_n$.

(2) Take p pairs of adjacent samples as sub-sample groups each time, thus obtaining a total of $n - p + 1$ sub-samples.

(3) Using $C = \lambda_0 + \lambda_1 R + e_R$ to sequentially fit the $n - p + 1$ group of sub-samples, then $\eta(R_i) = \hat{\lambda}_1^i$ for $i = 1,2,\cdots,n-p+1$.

The overall trends of $\eta(R_i)$ for $i = 1,2,\cdots,n-p+1$ is decreasing, but the rate of deceasing gets smaller as time travels. Also, $\eta(R) = \rho(r)\exp\{-\frac{1}{N}\int_0^R \rho(\mu)d\mu\}$. Based on such two aspects, we use the exponential function to fit $\eta(R)$.

$$g(R) = \exp\{\beta_0 + \beta_1 R + \beta_2 R^2\}$$

The numerical analysis results show that for the three-parameter exponential function, the estimation of β_2 in different regions are almost not significant at the 0.05 level of significance. Therefore, we consider using the two-parameter exponential function as the fitting function

$$h(R) = \exp\{\beta_0 + \beta_1 R\}$$

From the above equation, we obtain the following regression model

$$\ln(\eta(R)) = \beta_0 + \beta_1 R + e_R$$

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where e_R is the error, $\{\beta_0, \beta_1\}$ are parameters to be estimated.

The reported numbers of the infected and recovered cases are subject to measurement errors. In general, the late reported data is more reliable than early reported data, thus we use the non-negative constraint weighted least squares method to estimate parameters

$$\arg\min_{\beta_0,\beta_1} \sum_{i=1}^{n-p+1} \omega_i \left[\ln\left(\eta(R_i) - (\beta_0 + \beta_1 R_i)\right)\right]^2, s.t. \beta_1 < 0$$

where $R_1 < R_2 < \cdots < R_{n-p+1}$ are selected samples, $\omega_i = \exp\{-\lambda(n-p+1-i)\}$ for $i = 1,2,\cdots,n-p+1$ are the weights to quantify the reliability of data, we take $\lambda = 0.1$ here.

After getting the fitting function of $\eta(R)$, we bring it to the differential equation and obtain

$$\frac{dC}{dR} = \hat{\eta}(R)$$

Since the number of hospitalized people is $H = C - R$, the trend of hospitalized people can be predicted after obtaining $C(R)$ for each R by solving the above equation.

3.2 Hospital Beds Estimation

The hospital bed density data (per 10000 population) by country is obtained from World Health Organization [10]. The Annual total population at mid-year by region, subregion and country comes from Department of Economic and Social Affairs Population Dynamics of United nations [11]. Let pop_i^t denote the population of country i at year t, and ρ_i^t denote the hospital bed density data for country i at year t. Thus, the number of hospital beds capacity for country i at year t is

$$Bed_i^t = pop_i^t * \rho_i^t$$

However, the hospital beds capacity data is only available before 2015 for several countries because of the availability of hospital bed density data. Considering the association of beds capacity and year in a short period, the number of hospital beds capacity at 2020 is assessed by the linear regression. Three possible regression models are tested, and then the best model is selected for each country using the Akaike Information Criterion.

$$\begin{cases} Bed_i = \beta_0 + \beta_1 t + \varepsilon_i \\ Bed_i = \beta_0 + \beta_1 t^2 + \varepsilon_i \\ Bed_i = \beta_0 + \beta_1 t + \beta_1 t^2 + \varepsilon_i \end{cases}$$

where Bed_i is the hospital beds capacity of country i, t is year, and ε_i is the error of country i.

For countries with the size of sample greater than three, we use the regression method to estimate the bed capacity at 2020, otherwise, we use the hospital beds capacity of the latest year instead.

4. Results

Based on the time-varying SIR dynamic model [5] and constrained weighted least squares method, a novel differential equation model is derived to predict the accumulated confirmed patients at the end of first wave COVID-19 pandemic and maximum hospital beds demand for each LMIC. We show the results of model prediction later. All analysis was performed in R (version 3.6.2).

4.1 Selection of Low- and Middle-income Countries

We identify LMICs according to the criteria of the World Bank and the United Nations. The detailed selection process is shown in the Figure 1. Finally, 58 LMICs are included in our analysis. We study these countries in the following sections.

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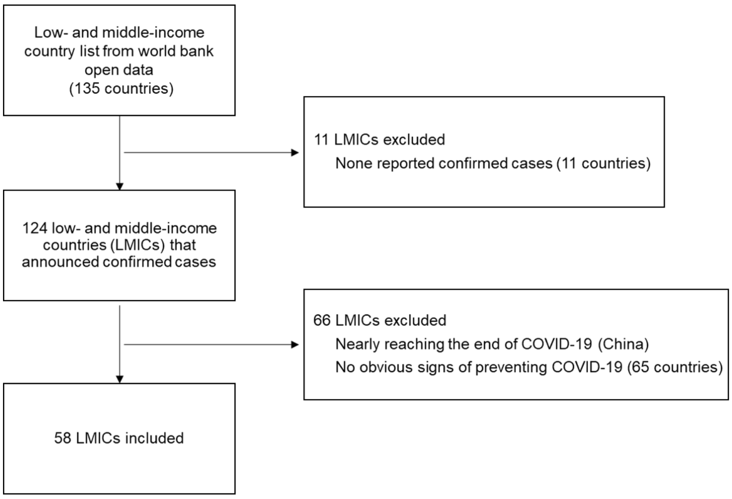

Fig. 1 Flow chart of selecting low- and middle-income countries

4.2 Estimation Results of Hospital Beds

Based on the selected countries, we further collect historical data on medical resources of these countries, including the number of beds and population. Due to the serious missing data in some countries, we do appropriate data preprocessing and use the regression model mentioned above for prediction. Regression model is used to predict hospital beds supply in 2020 for each LMIC. The results of prediction is shown in Table 1.

Table 1 Estimated Number of Hospital Beds for Low- and Middle-Income Countries (LMICs)

Country*	Hospital Beds Estimation	Most Updated year
Brazil	375239	2020
Russia	1056342	2020
India	875202	2011
Colombia	70452	2014
South Africa	134066	2005
Argentina	282386	2020
Bangladesh	125005	2015
Turkey	282109	2020
Iraq	56355	2020
Pakistan	117183	2014
Indonesia	310060	2015
Ecuador	23561	2013
Ukraine	396319	2020
Bolivia	12865	2020
Kazakhstan	77886	2020
Egypt	144679	2014
Belarus	134799	2020
Armenia	17633	2020
Azerbaijan	44112	2013
El Salvador	20901	2020
Bosnia and Herzegovina	12944	2020
Cameroon	26444	2010
Bulgaria	67461	2020
Kosovo	NA	NA
Madagascar	4230	2010

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North Macedonia	9135	2013
Congo, Dem. Rep.	45262	2006
Haiti	7280	2013
Guinea	3126	2011
Malaysia	57515	2015
Gabon	1974	2008
Mauritania	1245	2006
Malawi	19451	2011
Central African Republic	4419	2011
Zimbabwe	21920	2011
Djibouti	1354	2020
Suriname	1640	2010
Montenegro	2353	2020
Congo, Rep.	5796	2005
Cabo Verde	1035	2010
Eswatini	2251	2011
Thailand	137374	2005
Mozambique	16931	2011
Mali	1505	2010
South Sudan	NA	NA
Somalia	21852	2020
Angola	15547	2005
Benin	4600	2010
Guinea-Bissau	1484	2009
Sierra Leone	2332	2006
Yemen	22023	2020
Lesotho	2587	2006
Liberia	3113	2010
Chad	4039	2005
Sao Tome and Principe	535	2011
Eritrea	2250	2011
Cambodia	12417	2015
Mongolia	19773	2012

*For some LMICs, the data of hospital beds is not enough to estimate beds in 2020, therefore their hospital beds in most updated year is used here.

†The peak bed utilization rates for Kosovo and South Sudan were NA because the hospital bed density data for both of these countries were unavailable.

4.3 Estimation of Medical Resource Utilization

The study uses data including confirmed COVID-19 patients, recovered patients and deaths from January 22 to August 23, 2020 from Johns Hopkins University [12]. Estimated infections, infection rate, maximum hospital demand and hospital bed utilization rate for 58 low- and middle- income countries are listed in Table 2, which are the results of dynamic models. COVID-19 confirmed rate (per 100,000 population) is also calculated by dividing accumulated confirmed patients by total population for each LMIC. Maximum hospital bed utilization rate is calculated by dividing maximum hospital bed demand by total hospital bed.

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Table 2 Estimated infections, infection rate, maximum hospital demand and hospital bed utilization rate for 58 low- and middle- income countries

Country*	Ultimate number of infections† (95 % CI)	Infection rate ‡ (95% CI)	Peak hospital bed demand (95% CI)	Peak bed utilization rate ¶, % (95% CI)
Brazil	4755038 (3389582-6836111)	2237 (2237-3216)	860141 (530827-1411685)	229.2% (141.5%-376.2%)
India	5310052 (4120262-7069537)	385 (385-512)	760435 (550084-1083622)	86.9% (62.9%-123.8%)
Russia	1222448 (909616-1722461)	838 (623-1180)	280121 (212255-405096)	26.5% (20.1%-38.3%)
Colombia	718864 (563585-939643)	1413 (1108-1847)	204771 (148762-287534)	290.7% (211.2%-408.1%)
South Africa	691904 (548224-891166)	1167 (924-1503)	182658 (134329-260698)	136.2% (100.2%-194.5%)
Argentina	470229 (346140-664273)	1040 (766-1470)	149552 (99858-231018)	53.0% (35.4%-81.8%)
Bangladesh	460813 (320694-691391)	280 (195-420)	169624 (104679-284335)	135.7% (83.7%-227.5%)
Turkey	371414 (198742-767806)	440 (236-910)	85948 (41181-217849)	30.5% (14.6%-77.2%)
Iraq	338902 (210735-595473)	843 (524-1480)	64260 (33392-132675)	114.0% (59.3%-235.4%)
Pakistan	325813 (244768-566273)	147 (111-256)	105355 (105224-146582)	89.9% (89.8%-125.1%)
Indonesia	223639 (174210-296642)	82 (64-108)	46163 (34707-64345)	14.9% (11.2%-20.8%)
Ecuador	211443 (124276-385102)	1198 (704-2183)	108019 (52847-227325)	458.5% (224.3%-964.8%)
Ukraine	204554 (109943-499137)	468 (251-1141)	61360 (27740-174987)	15.5% (7.0%-44.2%)
Bolivia	163772 (116515-244605)	1403 (998-2095)	67220 (44257-108563)	522.5% (344.0%-843.9%)
Kazakhstan	124112 (73272-326767)	661 (390-1740)	46128 (34497-154192)	59.2% (44.3%-198.0%)
Egypt	102468 (84457-126386)	100 (83-124)	55736 (43160-73491)	38.5% (29.8%-50.8%)
Belarus	76468 (63414-93142)	809 (671-986)	24146 (19401-30898)	17.9% (14.4%-22.9%)
Armenia	50174 (36709-72889)	1693 (1239-2460)	13245 (9981-20254)	75.1% (56.6%-114.9%)
Azerbaijan	37082 (29206-47166)	366 (288-465)	7678 (5291-11077)	17.4% (12.0%-25.1%)
El Salvador	27988 (23750-42838)	432 (366-660)	12157 (11155-22505)	58.2% (53.4%-107.7%)
Bosnia and Herzegovina	22776 (16589-32843)	694 (506-1001)	7153 (4632-12008)	55.3% (35.8%-92.8%)
Cameroon	20491 (9452-48907)	77 (36-184)	4970 (1712-15845)	18.8% (6.5%-59.9%)
Bulgaria	18104 (10635-34145)	261 (153-491)	4674 (2268-10480)	6.9% (3.4%-15.5%)
Kosovo	16925 (9331-44195)	935 (515-2440)	4324 (2485-14809)	NA

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Madagascar	16292 (12167-23137)	59 (44-84)	3895 (2941-6085)	92.1% (69.5%-143.9%)
North Macedonia	16126 (11109-25294)	774 (533-1214)	4849 (3093-8941)	53.1% (33.9%-97.9%)
Congo, Dem. Rep.	15404 (10059-24835)	17 (11-28)	8039 (4597-14847)	17.8% (10.2%-32.8%)
Haiti	15085 (8023-36183)	132 (70-317)	10384 (5198-28002)	142.6% (71.4%-384.6%)
Guinea	12938 (6993-26125)	99 (53-199)	2597 (1127-6531)	83.1% (36.1%-208.9%)
Malaysia	11848 (5188-31564)	37 (16-98)	2487 (1078-8830)	4.3% (1.9%-15.4%)
Gabon	10107 (7196-14809)	454 (323-665)	3479 (2287-5669)	176.2% (115.9%-287.2%)
Mauritania	8078 (5870-11265)	174 (126-242)	2910 (1875-4594)	233.7% (150.6%-369.0%)
Malawi	7913 (4164-23810)	41 (22-124)	2855 (1640-10074)	14.7% (8.4%-51.8%)
Central African Republic	7622 (4565-13944)	158 (95-289)	5966 (3344-11660)	135.0% (75.7%-263.9%)
Zimbabwe	6855 (4735-23624)	46 (32-159)	3044 (2902-11898)	13.9% (13.2%-54.3%)
Djibouti	5865 (3042-37044)	594 (308-3749)	1566 (1375-15882)	115.7% (101.6%-1173.0%)
Suriname	5860 (3062-15165)	999 (522-2585)	970 (470-3324)	59.1% (28.7%-202.7%)
Montenegro	5711 (3550-21575)	909 (565-3435)	2099 (2007-6204)	89.2% (85.3%-263.7%)
Congo, Rep.	5554 (2458-20810)	101 (45-377)	2379 (852-10812)	41.0% (14.7%-186.5%)
Cabo Verde	5057 (2015-20233)	910 (362-3639)	889 (276-4713)	85.9% (26.7%-455.4%)
Eswatini	4972 (3143-8365)	429 (271-721)	1564 (809-3184)	69.5% (35.9%-141.4%)
Thailand	4877 (2096-33185)	7 (3-48)	1225 (953-9424)	0.9% (0.7%-6.9%)
Mozambique	4578 (2730-38333)	15 (9-123)	1952 (1554-25988)	11.5% (9.2%-153.5%)
Mali	3711 (1754-8522)	18 (9-42)	662 (221-2029)	44.0% (14.7%-134.8%)
South Sudan	3546 (1727-45702)	32 (15-408)	2208 (1315-32681)	NA
Somalia	3539 (2743-4916)	22 (17-31)	1986 (1544-2885)	9.1% (7.1%-13.2%)
Angola	3303 (1265-18649)	10 (4-57)	1680 (533-12734)	10.8% (3.4%-81.9%)
Benin	2959 (1779-5745)	24 (15-47)	1575 (810-3732)	34.2% (17.6%-81.1%)
Guinea-Bissau	2916 (1666-7850)	148 (85-399)	1900 (1132-5642)	128.0% (76.3%-380.2%)
Sierra Leone	2455 (1256-5867)	31 (16-74)	500 (260-1465)	21.4% (11.1%-62.8%)
Yemen	2444 (1253-6391)	8 (4-21)	631 (364-2035)	2.9% (1.7%-9.2%)
Lesotho	1517 (1039-2333)	71 (49-109)	867 (543-1449)	33.5%

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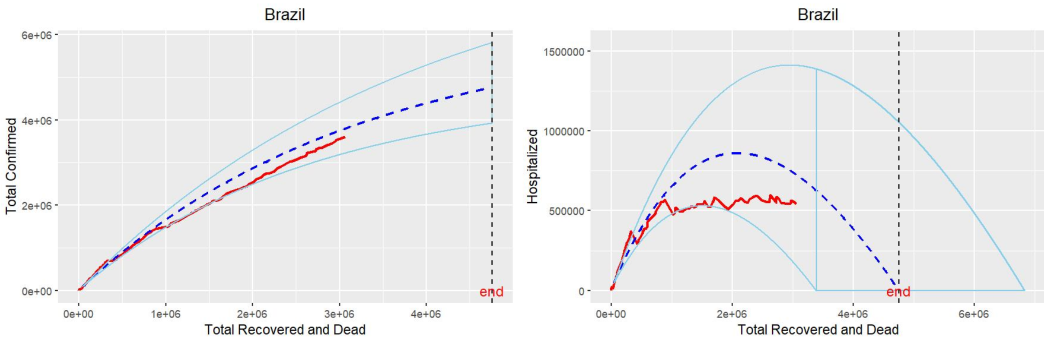
				(21.0%-56.0%)
Liberia	1422 (949-2749)	28 (19-54)	526 (362-1322)	16.9% (11.6%-42.5%)
Chad	1209 (538-6093)	7 (3-37)	324 (238-2213)	8.0% (5.9%-54.8%)
Sao Tome and Principe	855 (681-2454)	390 (311-1120)	464 (464-570)	86.7% (86.7%-106.5%)
Eritrea	481 (246-3468)	14 (7-98)	240 (159-2627)	10.7% (7.1%-116.8%)
Cambodia	361 (171-44021)	2 (1-263)	140 (38-43430)	1.1% (0.3%-349.8%)
Mongolia	288 (169-2537)	9 (5-77)	116 (115-813)	0.6% (0.6%-4.1%)

*The list of low- and middle-income countries was obtained from World Bank Open Data. The hospital bed density data by country came from World Health Organization. The Annual Total Population across countries came from United Nations.
†Ultimate number of infections was defined as the number of people infected with COVID-19 at the end of the epidemic.
‡Infection rate was defined as the ultimate number of Infections per 100,000 in the country. Infection rate (per 100,000 in the country) = 100,000 × (Number of Infections / total population of the country).
¶Peak bed utilization rate = Peak hospital bed demand / National hospital bed capacity. The peak bed utilization rates for Kosovo and South Sudan were NA because the hospital bed density data for both of these countries were unavailable.

Due to space constraints, we only show the forecast of epidemic development for several typical countries in Figure 2. At the peak of the epidemic, Bolivia (522.5%, 95% CI 344.0%-843.9%), Ecuador (458.5%, 95% CI 224.3% -964.8%) and Colombia (290.7%, 95% CI 211.2%-408.1%) will have the highest hospital bed utilization rates. Of all the 58 LMICs, 48.2% will have more than half of hospital beds occupied by COVID-19 patients. At the end of the first wave, it is estimated that India (5310052, 95% CI 4120262-7069537), Brazil (4755038, 95% CI 3389582-6836111) and Russia (1222448, 95% CI 909616- 1722461) will have the highest accumulated confirmed patients among all the LMICs. Specifically, Brazil will finally report the highest COVID-19 confirmed rate (per 100,000 population) with 2237 (95% CI 2237-3216). The confirmed rate will also be high in Armenia (1693, 95% CI 1239-2460) and Colombia (1413, 95% CI 1108-1847). 58.6% of the 58 LMICs are estimated to have confirmed rate of more than 100 per 100,000 population.

Fig.2 Forecast of epidemic development for several typical Low- and Middle-Income Countries (LMICs)



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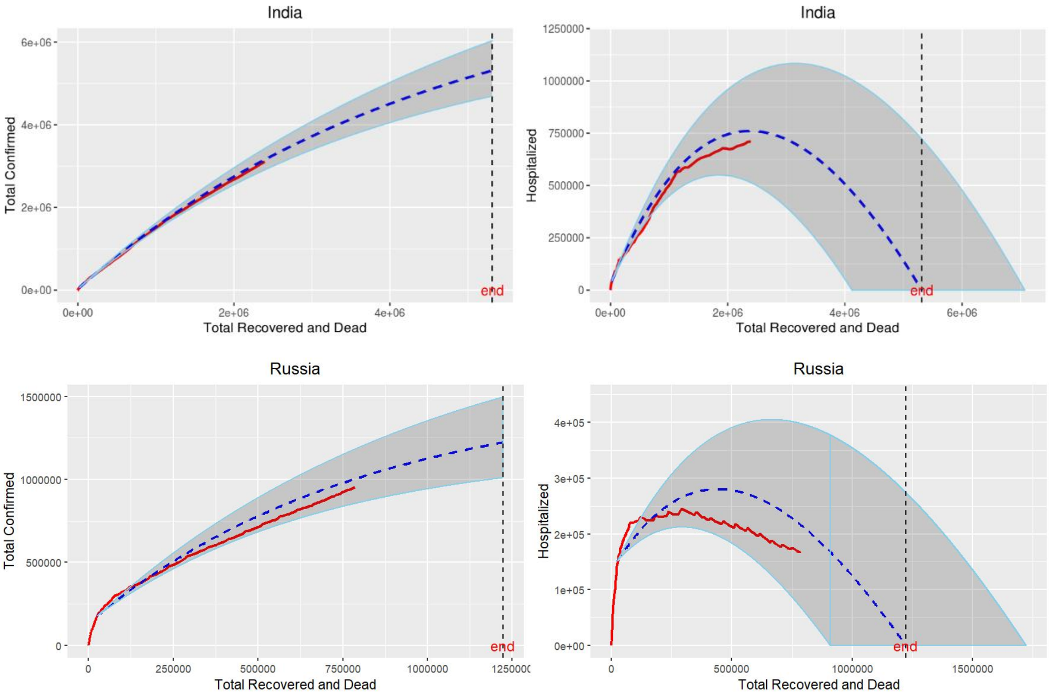

5. Summary

The epidemic is estimated to impose health care burden excessively exceeding the current capacity of hospitals in many LMICs. Effective non-pharmaceutical public health interventions, including cordons sanitaire, traffic restriction, social distancing, home confinement, centralized quarantine, and universal symptom survey, should be implemented to control the spread of COVID-19 [13]. In the case of uncontrollable outbreak, short-term strategies including reducing non-COVID-19 demand for health services and building mobile hospital to temporally mitigate the hospital system overload should also be recommended [14]. However, limited health care budgets in these regions may hinder the implementation of these strategies. Economic and medical assistance from more developed countries, WHO and other international NGOs will be much required for effective disease control in the LMICs.

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