

# Projection of COVID-19 intensive care hospitalizations in the Federal District, Brazil: an analysis of the impact of social distancing measures

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## Abstract

**Objective:** To build scenarios and analyze the impact of social distancing policies on the spread of COVID-19 and the need for intensive care unit beds. **Methods:** Three dissemination scenarios were built according to level of adherence to social distancing measures in the context of Brazil's Federal District, based on a dynamic transition compartmental model and Monte Carlo simulations. The model's parameter values were based on official sources, indexed bibliographic databases and public data repositories. **Results:** The favorable scenario, with constant 58% adherence to social distancing, estimated a peak of 189 (interquartile range [IQR]: 57 – 394) ICU hospitalizations on March 3<sup>rd</sup> 2021. Absence of social distancing would result in an unfavorable scenario with a peak of 6,214 (IQR: 4,618 – 8,415) ICU hospitalizations probably as soon as July 14<sup>th</sup> 2020. **Conclusion:** The projections indicate the high impact of social distancing measures and emphasize the applicability of public indicators for COVID-19 monitoring.

**Keywords:** Coronavirus Infections; Intensive Care Units; Bed Occupancy; Health Evaluation; Public Policy.

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## Introduction

COVID-19 is a disease resulting from Sars-CoV-2 virus infection. Its clinical manifestations can include severe acute respiratory syndrome (SARS), among others.<sup>1</sup> The first case in Brazil was confirmed on 25/2/2020; by 3/5/2020 the country had officially registered over 100,000 cases and 7,000 deaths.<sup>2</sup> Given its far-reaching nature and ability to spread rapidly, its potential to bring the hospital network to a collapse, in particular insufficient availability of intensive care unit (ICU) beds, COVID-19 is considered to be a very serious health condition for Public Health.<sup>1</sup>

*In scenarios with temporal limitation of data availability, building models and counterfactuals is of great value for identifying trends and projections of possible impacts of a given public policy.*

Although there are reports of experiments with treatment and initiatives to find a vaccine, at the time of writing this manuscript, there was no robust proof of the efficacy of pharmaceutical interventions in preventing or treating this clinical condition.<sup>3</sup> Ample testing, personnel protection (health services and essential services), isolation of infected individuals and adoption of non-pharmaceutical interventions, such as public policies on social distancing, appear as the most feasible option for addressing COVID-19.<sup>4</sup> On 11/3/2020, the first local social distancing measures came into force throughout Brazil's Federal District in view of the risk of novel coronavirus infection, including the suspension of events with audiences of more than 100 people and educational activities at all schools, universities and faculties.<sup>5</sup> Moreover, bars and restaurants had to ensure a minimum distance of two meters between tables. On 21/4/2020, in addition to the measures already taken, the Federal District government began testing symptomatic people, increasing sample collection and screening points exclusively for these people in places other than health centers.

With the aim of monitoring and informing public policy decisions on COVID-19, a series of initiatives and networks have joined forces and made available case prediction tools including projections of the need for

hospital beds and equipment.<sup>6-8</sup> In this respect, analysis of data on public policies, with regard to evaluation of their impact, is a field of possible inferences, for which robust data are essential. In scenarios with temporal limitation of data availability, building models and counterfactuals (possible but not necessarily observed scenarios) is of great value for identifying trends and projections of possible impacts of a given public policy.<sup>9</sup>

Based on the context of the occurrence of COVID-19 cases among the Federal District population, the objective of this study was to build scenarios to analyze the impact of social distancing policies on the spread of COVID-19 and the need for ICU beds in the Federal District, with the aid of a mathematical model and Monte Carlo simulations.

## Methods

Taking as our reference the bases and designs of studies in the field of public policy evaluation,<sup>9</sup> this is a case study based on simulations. Following data and indicator acquisition, we built scenarios of projections and counterfactuals relevant for analysis of the impact of social distancing on the demand for ICU beds in the context observed.

The case used for this analysis is comprised of all the administrative regions within the Federal District, the total population of which is estimated as being 3,223,048 inhabitants in 2020, according to projections made by the Brazilian Institute of Geography and Statistics (IBGE).<sup>10</sup> With the aim of obtaining a reference as to existing hospital capacity, we consulted the database of the National Registry of Health Establishments as at June 2020 to find the number of adult ICU beds in the Federal District. In addition, with the aim of contextualizing the adherence of the population to the social distancing measures recommended by the policies in force, we consulted the public data contained in the Federal District 'social isolation index' for the period 1/3/2020 to 31/7/2020, made available by the Inloco technology company.<sup>11</sup> This index has assisted initiatives monitoring the spread of COVID-19, undertaken by public universities and governmental institutions. By using telephone device geolocation data for part of the local population – with prior authorization –, it is possible to estimate on a daily basis the percentage of that population which has adhered to public policy advice on social isolation.<sup>11</sup>

## Model structure

A mathematical model was built in order to estimate the need for ICU beds as a result of the spread of COVID-19. Taking the methodological guidelines published by the Health Ministry's Science, Technology and Strategic Supplies Secretariat<sup>12</sup> and the practical bases for modeling communicable diseases,<sup>13</sup> the concept used for the model was a dynamic transition compartmental model. In this model, derived from the classic SIR model ('susceptible, infected and recovered') proposed by Kermack & McKendrick, transition between compartments (or states of health) is represented by a system of dependent differential equations, among other parameters, containing the number of infected people ( $I$ ), transmission coefficient ( $\beta$ ), latency ( $\alpha$ ) and recovery ( $\gamma$ ).

The transition and compartment structure used by this study was based on models already provided by other authors who also sought to project hospital demand,<sup>14-16</sup> as well as the impact of non-pharmaceutical interventions – such as use of facemasks – on community transmission of COVID-19.<sup>17</sup> In this proposal, the model for the daily correlation between the number of susceptible ( $S$ ), exposed ( $E$ ), infected ( $I$ ) and removed ( $R$ ) individuals – SEIR – is represented in Figure 1.

Within the infected compartment, there are also subdivisions of those who do not need to be hospitalized ( $I_1$ ), those who progress to needing hospitalization ( $I_2$ ) and patients in a critical state ( $I_3$ ) who need to be hospitalized in an ICU.

## Main premises of the model

- No change in the total size of the population is expected (overall birth and mortality rates), except due to death from COVID-19. Given the short time period analyzed, this restriction was considered to simplify the model with little impact on the results.
- Similarly to previous approaches, based on COVID-19 SEIR models,<sup>17</sup> it is assumed that hospitalized individuals are not effectively exposed to the general population and, therefore, do not contribute to the calculation of the force of infection in the community.
- The possibility of a recovered individual being reinfectd is not foreseen, even though there is no conclusive evidence as to the extent to which acquired immunity following infection protects against reinfection.<sup>18</sup>

- As it is not an objective of the analysis, this model does not take into consideration potential increase in mortality due to lack of hospital beds. It is important to note that lethality found by the model may be underestimated in a scenario of lack of hospital beds.
- The estimates of effective contact assume random mixing,<sup>13</sup> whereby each infected individual may have contact with a susceptible individual according to the same average probability.

The complete equations and further details of the model are provided in Supplementary Material 1.

## Scenarios

Three scenarios of the spread of COVID-19 were built with the aim of analyzing the potential impact of the disease on the need for hospital care. The scenarios were based on a one-year time period which was considered to be sufficient to take into account both a complete wave of infections and also uncertainty as to availability or otherwise of specific interventions (vaccines and treatment). The start date was 22/3/2020, providing a ten-day margin between the beginning of the social distancing measures and the peak of social isolation levels obtained in the Federal District.

### Scenario A – COVID-19 spread profile with no adherence to social distancing measures

#### Definition

This scenario represents the contrafactual that would occur if no social distancing measures were taken or adhered to by the population.

There is therefore no reduction in social contact over the course of the model, taking an average estimate of social isolation observed in the last ten days before the local measures were brought into force on 11/3/2020.

The model therefore uses a constant transmission coefficient ( $\beta$ ) value.

### Scenario B – COVID-19 spread profile maintaining adherence to social distancing

#### Definition

This scenario represents the profile of the spread of infection and the profile of need for hospital beds

maintaining the same level of average social isolation obtained during the first ten days after the peak in social isolation.

In this scenario, the model also uses a constant transmission coefficient ( $\beta$ ) value.

### **Scenario C – COVID-19 spread profile based on the observed dynamics of a falling level of social distancing**

#### *Definition*

This scenario represents the dynamics of social isolation observed in the Federal District and the possible projection of the need for hospital beds when maintaining the last average levels of isolation observed.

Seeking to simulate an interruption or return of distancing measures, this context also estimates population isolation targets according to demand for ICU beds.

As mentioned in the definitions presented, the scenarios did not include a complete simulation of adherence to distancing above the average observed following the implementation of distancing policies in the Federal District. Despite this, we emphasize that the analysis of the isolation measures in Scenario C was not subject to this restriction.

#### **Parameter values and uncertainties**

With the aim of bringing the analysis model closer to local reality and to the size of the population, we used the Federal District age structure to adjust the expected indicators of lethality and hospitalization for the region. Federal District Health Department official bulletins<sup>19</sup> were used to obtain numbers of cases by date of symptom onset, numbers of ICU hospitalizations and COVID-19 deaths in the Federal District. In addition to the estimates of infection and lethality by age group for the Federal District (Supplementary Material 2), the complete series of ICU hospitalizations, deaths and percentage social isolation available for the period analyzed (data from 1/3/2020 to 31/7/2020) is shown in Supplementary Material 3. In addition to the parameters mentioned, the daily evolution of the instantaneous reproduction number ( $R_t$ ) was estimated for each scenario.

Given the absence of local data for the remaining parameters, we also consulted publications indexed on Pubmed (<http://www.ncbi.nlm.nih.gov/pubmed>), preprints

on MedRxiv ([www.medrxiv.org](http://www.medrxiv.org)) and public repositories of modeling parameters, such as the initiative of the MIDAS network (<http://midasnetwork.us/COVID-19>), using an adaptation of the basic search structure with the terms (COVID-19 OR coronavirus) AND (model OR modelling). The choice of the data sources of available parameters prioritized those used in models validated by other institutions considered to be references on the subject, such as the Imperial College London models, seeking comparability of the model proposed here. The retrieved data included point estimations and their parametric uncertainties (standard error, confidence intervals or probability distributions). The values of the main parameters considered in model proposed here, along with their parametric uncertainties, description and sources, are shown in Table 1.

In order to take into consideration the impact of the parametric uncertainties of the nine parameters described in Table 1 on the model results, the analyses were performed using a stochastic (probabilistic) approach, using Monte Carlo simulations, with multiple draws on expected value levels (2<sup>nd</sup> order).<sup>20</sup> Based on the characteristics of the variables, *a priori* probability distributions were adjusted for the following parameters: incubation time (days), duration of mild clinical picture (days), fraction of individuals with a severe clinical picture (%), time hospitalized in a ward (days), fraction of individuals who progressed to ICU hospitalization UTI (%), time hospitalized in an ICU (days), lethality (%) and time from onset of symptoms to death (days), as illustrated in Supplementary Material 4. In the absence of intervals in the data sources, we used bootstrap resampling to estimate parametric uncertainty (confidence intervals). The results were summarized into medians and coverage amplitudes of the simulations (interquartile range [IQR] and confidence interval [CI]).

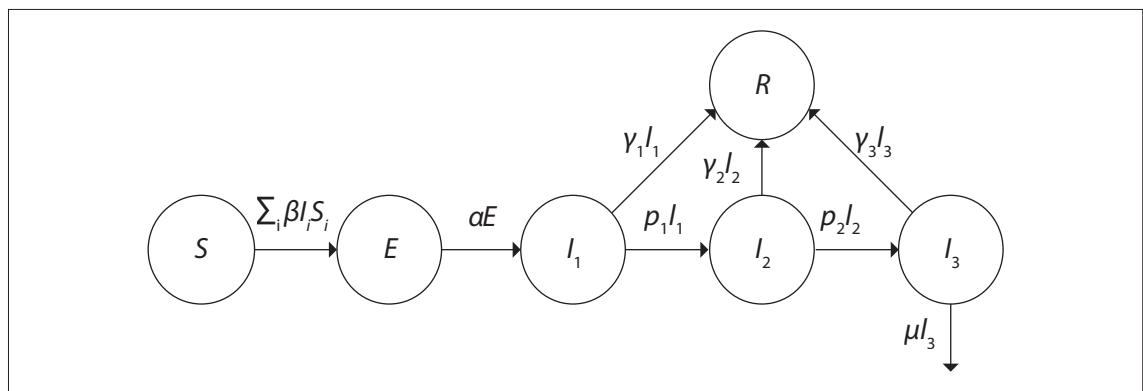
#### **Validation**

In order to calibrate the model, we used as a reference the scenario that reflects the spread of COVID-19 during the observed levels of social distancing (Scenario C). We recorded the values of the minimization statistic of the root-mean-square error (RMSE) of the number of deaths predicted by the model, as observed in the time series under analysis. The adequacy of the number of Monte Carlo simulations was assessed by visual inspection of the convergence of the main parameters of the model.

**Table 1 – List of values, parametric uncertainties, distributions and sources of the main parameters of the model of the spread of COVID-19 in the Federal District, Brazil**

Parameter	Point estimation	Lower limit	Upper limit	Probability function	Description	Source
Incubation (days)	5.10	4.50	5.80	Lognormal	Incubation time	Sanches et al. <sup>26</sup>
Duration – mild (days)	3.65	3.21	4.09	Gama	Duration of condition until isolation or hospitalization	Linton et al. <sup>27</sup>
Severe clinical picture (%)	4.57	2.72	9.32	Beta	Proportion of infected people who will have severe or critical clinical picture (hospitalization)	Verity et al. <sup>28</sup>
Length of hospitalization (days)	8.00	6.00	10.00	Lognormal	Average length of hospitalization in a ward	Ferguson et al. <sup>29</sup>
ICU <sup>a</sup> hospitalization (%)	46.30	44.31	48.06	Beta	Percentage of severe patients needing intensive care	Epidemiological Bulletins <sup>19</sup>
Time in ICU <sup>a</sup> (days)	9.00	6.00	13.00	Lognormal	Average length of hospitalization in ICU <sup>a</sup>	Grasselli et al. <sup>30</sup>
Lethality (%)	0.576	0.315	1.140	Beta	Lethality of infected people adjusted for the region	Verity et al. <sup>28</sup>
Time until death (days)	17.80	16.02	19.58	Lognormal	Average time from symptom onset to death	Verity et al. <sup>28</sup>
ICU <sup>a</sup> mortality (%)	27.23	12.85	47.81	Not applicable	Probability of death in ICU <sup>a</sup>	Calibrated by lethality

a) ICU: intensive therapy unit.



Source: Adapted from Hill.<sup>15</sup>

**Figure 1 – Representation of the structure of the compartmental dynamic model used**

All the analyses were performed with the aid of Microsoft Excel® and the Visual Basic for Applications (VBA) programming language. The adjustment of the calibration parameters was performed using the non-linear least squares method, with the support of the non-linear Generalized Reduced Gradient (GRG) optimization algorithm, using the SOLVER function. The complete model and the history of its versions are available at a public data repository.<sup>21</sup>

## Results

According to the official data consulted, between 1/3/2020 and the final date of data acquisition for the model (31/7/2020), 106,292 COVID-19 cases

and 1,469 deaths had been confirmed in the Federal District.<sup>19</sup> Bearing in mind the date of the first local decree on distancing measures, there was important initial adherence to the measures by the population, given the gradual increase in the rate of social isolation over the days following the decree, from an average of 30.0% between 2/3/2020 and 11/3/2020, to an average of 57.4% between 22/3/2020 and 30/4/2020 (Figure 2).

Considering the records of cases by date of symptom onset, all the scenarios began simulations on 22/3/2020, with an average estimate of 366 infected ( $I_1$ ) individuals and 732 exposed (E) individuals – given the existence of a minimum instantaneous reproduction number ( $R_t$ ) of 2 without social isolation. With an RMSE of 83.5 in the predicted death values, the value of parameter



$\tau$  was estimated as 0.6979 for calibrating the model. According to the National Registry of Health Establishments database, as at June the Federal District had a total of 1534 adult ICU beds, 378 of which were public. Below are the results of each of the scenarios.

**Scenario A – COVID-19 spread profile with no adherence to social distancing measures**

In the first scenario, the transmission coefficient is calculated assuming the level of social isolation to be 30.0%, this being coherent with the average values observed up until 11/3/2020. As illustrated in Figure 3, given the need to hospitalize critical cases, if there were no adherence to social distancing by the population, according to the median of the simulations, there would be a peak of 6,214 people needing to be hospitalized in ICUs (IQR: 4,618 – 8,415) probably on 14/7/2020 (IQR: 9/7/2020 – 20/7/2020). However, according to the National Registry of Health Establishments data, the total number of public ICU beds registered would already have been surpassed on 17/5/2020 (IQR: 12/5/2020 – 22/5/2020). This demand, greater than the number of registered public ICU beds, would continue for at least 125 days (IQR: 115 – 135).

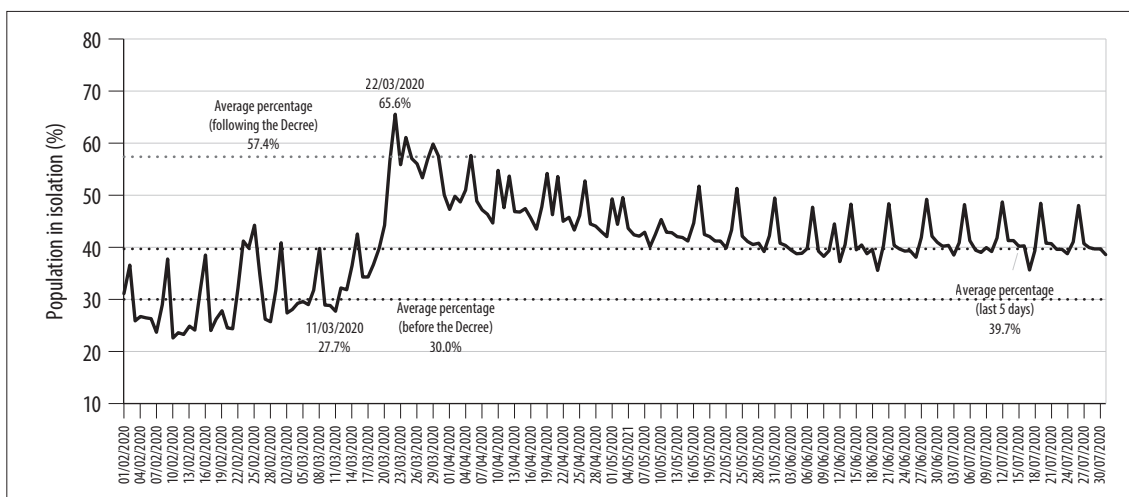
Over the period of a year, there would probably be a peak of 178,615 active infections (IQR: 153,820 –

203,955) on 1/7/2020 (IQR: 26/6/2020 – 6/7/2020). At this rate, by 31/3 of the following year (2021), up to 73.2% (IQR: 70.3 – 75.9%) of the Federal District population would have been infected. Even if it were possible to provide care for all infected people, 16,143 individuals would have died (IQR: 10,948 – 22,326) – expected lethality would be 0.67% (IQR: 0.45 – 0.94%).

**Scenario B – COVID-19 spread profile maintaining adherence to social distancing**

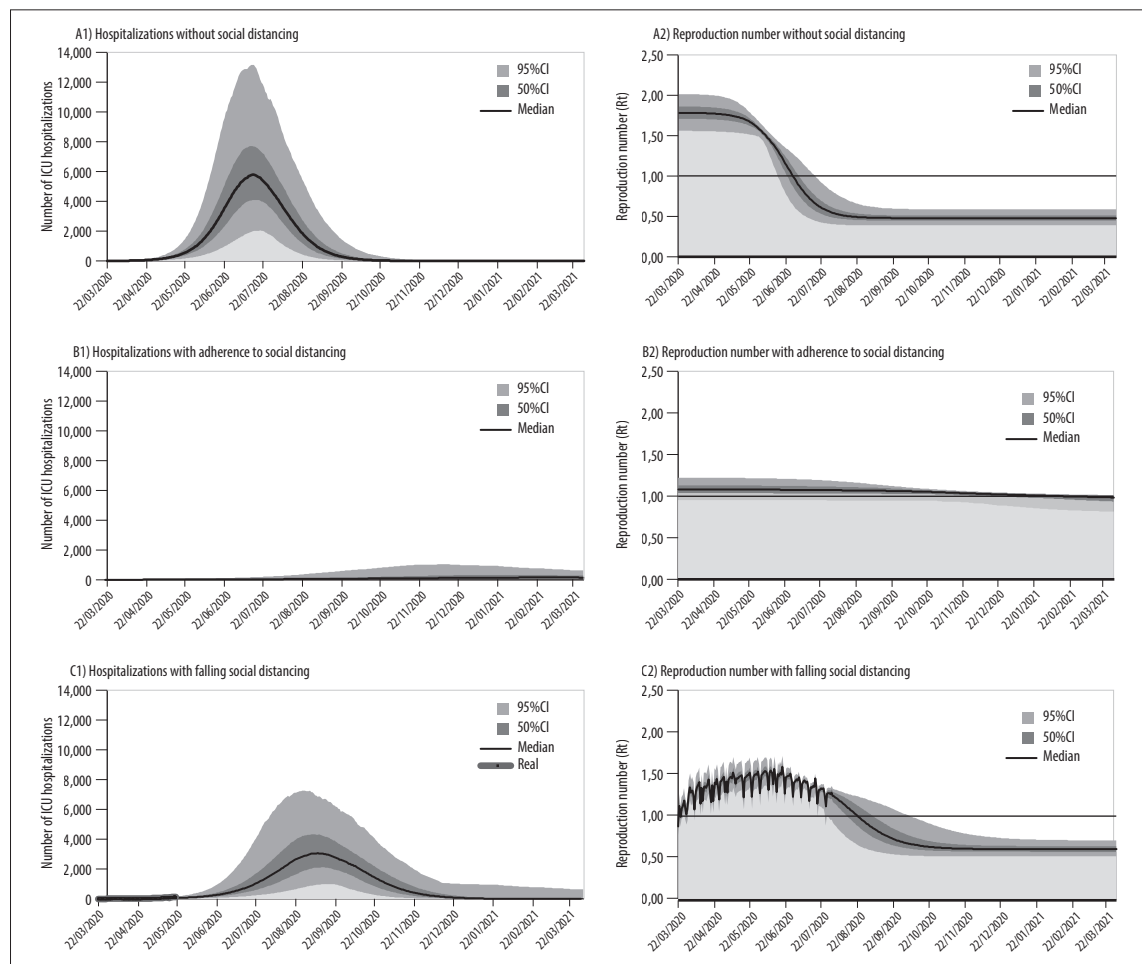
Considering the hypothesis of maintaining the average level of social isolation at 57.38%, this being the level reached in the initial period of the distancing measures, this scenario projected a peak of 189 ICU hospitalizations (IQR: 57 – 394) only on 7/3/2021 (IQR: 6/1/2021 – 31/1/2021) and, in this context, it would be feasible to meet the demand with the number of beds registered in the Federal District.

Over the one-year simulated period, the total number of infected individuals could reach a peak of 5,269 active infections (IQR: 1,538 – 11,549). By 31/3/2021, the cumulative total of infections would affect only 7.6% of the Federal District population DF (IQR: 3.0 – 16.4%) and, with 0.70% lethality (IQR: 0.47 – 0.94%), there would be up to 1,438 deaths (IQR: 583 – 3,234).



Source: InLoco public database data.<sup>11</sup>

**Figure 2 – Evolution of percentage social isolation in relation to the implementation date of COVID-19 combat measures in the Federal District, Brazil**



**Figure 3 – Projections of the demand for ICU beds due to COVID-19 and the instantaneous reproduction number ( $R_t$ ) in Scenario (A) COVID-19 spread profile with no adherence to social distancing measures, Scenario (B) COVID-19 spread profile maintaining adherence to social distancing and Scenario (C) COVID-19 spread profile based on the observed dynamics of a falling level of social distancing, in the Federal District, Brazil**

### **Scenario C – COVID-19 spread profile based on the observed dynamics of a falling level of social distancing**

Using the proposed methodology described for this scenario, the transmission coefficient followed the dynamic variation of the level of isolation recorded as at 31/7/2020. With effect from 1/8/2020, the average level of 39.7% isolation was assumed to continue, based on the levels recorded on the last five days available.<sup>11</sup> As such, the fall observed in the level of distancing was projected to lead to a peak of up

to 3,460 ICU hospitalizations (IQR: 2,634 – 4,779) probably on 10/9/2020 (IQR: 31/8/2020 – 22/9/2020) (Figure 3). In this scenario, even raising the level of isolation to an average of 70% (a level close to the maximum level recorded on 22/3/2020) with effect from 1/8/2020, there would still be a peak of 2,097 hospitalizations (IQR: 1.245 – 3.312) on 19/8/2020 (IQR: 16/8/2020 – 21/8/2020). On the other hand, complete interruption of distancing, returning to the 30% level of isolation observed before the distancing policies were implemented, would lead to a peak of 4,812 ICU hospitalizations (IQR: 3,643 – 6,283) on 12/9/2020 (IQR: 04/9/2020 – 21/9/2020).

## Discussion

Based on public indicators and data used in this analysis, it is possible to identify adherence to social distancing following the publication of the first decree establishing measures to address COVID-19 in the Federal District. Likewise, linking the temporal evolution of the level of isolation with the consequent progressive reduction in the spread of the disease ( $R_t$ ), it would be possible to reach reference values for the control of outbreaks and, at the same time, delay and reduce the peak of ICU hospitalizations to a plausible estimate in relation to the capacity of the local healthcare network.

Differently to the scenario in which social distancing was maintained, both the other scenarios with absence of social distancing, whether because of no measures being implemented (Scenario A), or because of low adherence (Scenario C), provide a projection compatible with the collapse of the local healthcare network due to high demand for ICU hospitalizations. Notwithstanding the uncertainty about the data and the magnitude of demand, the alternative projections of Scenario C, which seeks to incorporate the observed percentages of social isolation, pointed to peaks of hospitalization in August and September of this year. These projections are consistent with the ICU bed waiting list situation in the Federal District reported in August. Also coherent with the findings of a recent study of other Brazilian states carried out by researchers from Imperial College London,<sup>22</sup> notwithstanding significant reductions in the spread of cases, the levels of isolation achieved would perpetuate an  $R_t > 1$ , indicating the continuation of epidemic growth of COVID-19 in the Federal District.

Despite this analysis being restricted to the context of the Federal District, it shows the magnitude of the potential effect of distancing on the need for hospital beds, it being unlikely that this relationship, even with a different magnitude, cannot be generalized to other contexts. The results are also consistent with other initiatives analyzing social distancing,<sup>4</sup> including national contexts such as the analysis by *Rede CoVida* of the positive effects of social distancing and the reduction in movement of people between municipalities on the control of COVID-19 in the state of Bahia,<sup>6</sup> the available data of which strongly suggest that the measures taken managed to flatten the epidemic curve in that state.

The model adopted here follows methodological lines compatible with the population dynamics of infections<sup>13</sup> and, as much as possible, was built on local parameters,

including the adjustment of the infection and lethality rates to the Federal District age structure. Moreover, we sought to make transparent use of available evidence and deal in a robust manner with the parametric uncertainties by using Monte Carlo simulations.<sup>20</sup> As demonstrated in this analysis of the Federal District, monitoring dynamic indicators of isolation and spread of infection, such as estimated  $R_t$ , along with their uncertainties, is an efficient and pragmatic strategy for monitoring policies intended to address COVID-19.<sup>23</sup>

Despite compartmental models at expected levels being able to represent average behavior of epidemics in populations, they are not capable of portraying individual histories.<sup>12</sup> Likewise, estimating the dynamic values of the rates of effective contacts is discussed according to varied approaches in the literature, with different potential impacts on the results, depending on the calculation method.<sup>24</sup> Although the adjustments relating to local age structure and calibration based on available records of hospitalizations were taken into consideration, other factors capable of interfering in the projection scenarios were not taken into consideration, such as comorbidities related to greater severity of the disease, including cardiovascular, respiratory and endocrine diseases.<sup>25</sup> And still in relation to demographic and social characteristics, we emphasize that the model assumes the premise of random contact, and the values of its estimates may diverge from measurements obtained when considering the specific contact patterns of each group (influence of heterogeneity). When interpreting the number of deaths expected by the model, it is important to remember that we did not take into consideration the possibility of increased deaths because of lack of hospital beds in the event of a possible collapse of the health care network.

Finally, we highlight that the data shown here on registered beds should also be interpreted paying attention to the reference of the targets for reducing impact on the hospital network. This is because they do not take into consideration the real proportion of hospital bed occupancy due to other clinical conditions, nor additional beds that are being put in place by health authorities.

Despite its limitations, this analysis reinforces conclusions as to the positive effect of social distancing measures on reducing the impact of the spread of COVID-19 on demands on the hospital network. Given the alarming scenario projected in the event of interruption or low adherence to social distancing, it is essential that local health authorities consider daily



monitoring of distancing indicators, spread of the disease and availability of hospital beds, when planning and implementing public policies to combat COVID-19.

### Authors' contributions

Zimmermann I, Sanchez M and Alves D discussed and built the initial design of the study. Zimmermann I,

Sanchez M and Brant J worked on data acquisition and the concept of the model. Zimmermann I implemented the model, conducted the simulations and summarized the main results. All the authors contributed equally to discussion and critical assessment of the results and approved the final version of the manuscript. They are responsible for all aspects thereof, including the guarantee of its accuracy and integrity.

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## Supplementary Material 1 – Transitions and equations

Following contact with an infected person, an individual who up to then was susceptible ( $S$ ) becomes exposed ( $E$ ) during a period of latency. This period is related to average disease incubation time. Following the latency period, the individual becomes infectious ( $I_1$ ) and can spread infection before being hospitalized ( $I_2$  or  $I_3$ ) or being removed ( $R$ ) from circulation by being placed in quarantine. Hospitalization was foreseen for individuals who, following a mild clinical picture ( $I_1$ ), progressed to a severe clinical picture ( $I_2$ ) or a critical clinical picture ( $I_3$ ). In keeping with the follow-up of patients with COVID-19, in the case of patients who progress to a critical clinical picture, transition to death is foreseen according to specific lethality of the disease ( $\mu$ ). In each of the compartments of hospitalized individuals, the possibility is also foreseen of them being removed from the model depending on length of hospitalization ( $\gamma^i$ ). The transitions between the compartments were solved by a system of equations, whereby the total population ( $N$ ) is equal to and represents the sum of susceptible ( $S$ ), exposed ( $E$ ), infected ( $I$ ), removed ( $R$ ) and dead ( $M$ ) individuals at each moment in time  $t$  of the model. The model's differential equation system is shown in equations 1 to 8:

$$S(t+1) = S(t) - (\beta I_1) \frac{S(t)}{N} \quad (1)$$

$$E(t+1) = E(t) + (\beta I_1) \frac{S(t)}{N} - \alpha E(t) \quad (2)$$

$$I_1(t+1) = I_1(t) + \alpha E(t) - (\gamma_1 + p_1) I_1(t) \quad (3)$$

$$I_2(t+1) = I_2(t) + p_1 I_1(t) - (\gamma_2 + p_2) I_2(t) \quad (4)$$

$$I_3(t+1) = I_2(t) + p_2 I_2(t) - (\gamma_3 + \mu) I_3(t) \quad (5)$$

$$R(t+1) = R(t) + \gamma_1 I_1(t) + \gamma_2 I_2(t) + \gamma_3 I_3(t) \quad (6)$$

$$M(t+1) = M(t) + \mu I_3(t) \quad (7)$$

$$N = S(t) + E(t) + I_1(t) + I_2(t) + I_3(t) + R(t) + M(t) \quad (8)$$

Below we present equations that are complementary to the model's differential equation system, where  $f_{hosp}$  refers to the fraction of individuals who progressed to hospitalization,  $f_{uti}$  refers to the fraction of hospitalized individuals who progressed to a critical clinical picture, and  $ifr$  refers to lethality:

$$\alpha = (\text{incubation time})^{-1} \quad (9)$$

$$\delta = \frac{ifr}{(f_{hosp} f_{uti})} \quad (10)$$

$$\mu = \delta \frac{1}{\left( \frac{\text{time until death}}{\text{time until isolation or hospitalization}} - \frac{\text{time until isolation}}{\text{time until isolation or hospitalization}} \right)} \quad (11)$$

$$\gamma_1 = f_{hosp} (\text{time until isolation or hospitalization})^{-1} \quad (12)$$

$$\gamma_2 = (1 - f_{uti}) (\text{time in a regular bed})^{-1} \quad (13)$$

$$\gamma_3 = (1 - \delta) (\text{time in an ICU bed})^{-1} \quad (14)$$

$$p_1 = (\text{time until isolation or hospitalization})^{-1} - \gamma_1 \quad (15)$$

$$p_2 = f_{uti} (\text{time in a regular bed})^{-1} - \gamma_1 \quad (16)$$

## Relationship between social distancing and transmission coefficient

With the aim of simulating the spread of the disease in view of the effects of social distancing, we calculated the transmission coefficient ( $\beta$ ), based on available epidemic estimates and social isolation estimates.<sup>17,24</sup> As such, we take into consideration here the dynamic relationship whereby the effect contact rate ( $\beta$ ) at each moment in time follows the function of a transmissibility factor ( $\tau$ ), this being a more stable factor strongly associated with pathogen virulence, and the function of a exposed individual contact factor ( $c$ ), this being a more dynamic factor and dependent on social isolation, i.e.  $\beta = \tau c$ . As such, the isolation levels recorded daily in the Federal District time series, are imputed in the model as a complement of factor  $c$ . Likewise, similarly to what was proposed by Eikenberry et al.,<sup>17</sup> the value of  $\tau$  was estimated by means of calibration using the values of the time series of the number of ICU hospitalizations due to COVID-19 in the Federal District between 22/3/2020 and 21/5/2020.

Once the transmission coefficient  $\beta$  was obtained, we also calculated the instantaneous reproduction number ( $R_t$ ) for each day in the period analyzed, with the aim of illustrating the dynamics of the spread of COVID-19 as per the proposed scenarios. In keeping with previous methodological approaches, the instantaneous reproduction number ( $R_t$ ) considers the specific rates of entering and leaving the infectious compartment by means of equation 17:

$$R_t = \frac{\beta(t) S(t)}{(\rho_1 + \gamma_1)} \quad (17)$$

## Supplementary Material 2 – Infection, hospitalization and lethality rates expected for COVID-19, according to age structure, in the Federal District, Brazil

Age range (years)	Inhabitants	Frequency (%)	Infection rate (per 10,000 inhab.)	Hospitalization rate of infected people (%)	Lethality of infected people (%)
0-9	419,57	13.00	0.36	0.00	0.00
10-19	450,663	13.98	13.73	0.04	0.01
20-29	594,106	18.43	14.92	1.04	0.03
30-39	570,790	17.71	14.24	3.43	0.08
40-49	483,968	15.02	13.99	4.25	0.16
50-59	336,382	10.44	15.98	8.16	0.60
60-69	207,838	6.45	15.33	11.80	1.93
70-79	110,260	3.42	15.14	16.60	4.28
≥80	49,884	1.55	12.87	18.40	7.80
<b>Total</b>	<b>3,223,048</b>	<b>100.00</b>	<b>13.02</b>	<b>4.57</b>	<b>0.58</b>

Sources: Brazilian Institute of Geography and Statistics (IBGE)<sup>10</sup> and Verity et al.<sup>28</sup>



### Supplementary Material 3 – Time series of cumulative confirmed COVID-19 cases, intensive care hospitalizations, number of deaths and percentage social isolation in the Federal District, Brazil

Date	Cumulative cases	ICU <sup>a</sup> hospitalizations	Cumulative deaths	Percentage isolation
1/3/2020	1	–	–	0.4090
2/3/2020	1	–	–	0.2740
3/3/2020	1	–	–	0.2810
4/3/2020	1	–	–	0.2930
5/3/2020	1	–	–	0.2960
6/3/2020	1	–	–	0.2900
7/3/2020	1	–	–	0.3180
8/3/2020	1	–	–	0.3980
9/3/2020	1	–	–	0.2891
10/3/2020	1	–	–	0.2880
11/3/2020	2	–	–	0.2770
12/3/2020	2	–	–	0.3220
13/3/2020	2	–	–	0.3190
14/3/2020	6	–	–	0.3650
15/3/2020	8	–	–	0.4260
16/3/2020	13	–	–	0.3430
17/3/2020	22	–	–	0.3430
18/3/2020	26	–	–	0.3670
19/3/2020	42	–	–	0.3990
20/3/2020	87	–	–	0.4430
21/3/2020	100	–	–	0.5670
22/3/2020	117	1	–	0.6560
23/3/2020	133	1	1	0.5590
24/3/2020	177	1	1	0.6110
25/3/2020	182	6	1	0.5710
26/3/2020	201	6	1	0.5610
27/3/2020	241	8	1	0.5340
28/3/2020	260	13	1	0.5700
29/3/2020	298	19	2	0.5990
30/3/2020	312	20	2	0.5761
31/3/2020	333	30	3	0.5010
1/4/2020	370	30	4	0.4730
2/4/2020	400	41	6	0.4980
3/4/2020	419	40	9	0.4870
4/4/2020	456	38	10	0.5100
5/4/2020	468	41	12	0.5770
6/4/2020	485	37	12	0.4890
7/4/2020	503	40	12	0.4720
8/4/2020	509	42	13	0.4640
9/4/2020	527	35	14	0.4470
10/4/2020	556	33	14	0.5480
11/4/2020	592	32	14	0.4760
12/4/2020	618	33	16	0.5370
13/4/2020	641	30	17	0.4690
14/4/2020	651	28	19	0.4680
15/4/2020	688	30	22	0.4750
16/4/2020	727	29	22	0.4570
17/4/2020	756	25	24	0.4350
18/4/2020	796	26	24	0.4780
19/4/2020	860	28	24	0.5420
20/4/2020	875	28	24	0.4630
21/4/2020	913	29	24	0.5360
22/4/2020	959	30	25	0.4500

to be continue

continuation

Date	Cumulative cases	ICU <sup>a</sup> hospitalizations	Cumulative deaths	Percentage isolation
23/4/2020	968	30	26	0.4580
24/4/2020	1,012	32	26	0.4330
25/4/2020	1,020	34	27	0.4610
26/4/2020	1,125	34	27	0.5280
27/4/2020	1,189	35	28	0.4450
28/4/2020	1,230	36	28	0.4410
29/4/2020	1,313	38	28	0.4300
30/4/2020	1,423	38	30	0.4210
1/5/2020	1,546	43	31	0.4930
2/5/2020	1,605	45	32	0.4440
3/5/2020	1,720	49	33	0.4960
4/5/2020	1,793	59	33	0.4370
5/5/2020	1,837	56	34	0.4240
6/5/2020	2,046	60	35	0.4220
7/5/2020	2,258	60	35	0.4290
8/5/2020	2,442	64	37	0.4010
9/5/2020	2,576	66	39	0.4250
10/5/2020	2,682	72	42	0.4540
11/5/2020	2,799	78	44	0.4290
12/5/2020	2,979	87	46	0.4280
13/5/2020	3,192	92	48	0.4210
14/5/2020	3,416	94	51	0.4190
15/5/2020	3,786	86	55	0.4120
16/5/2020	4,140	84	56	0.4472
17/5/2020	4,368	116	59	0.5176
18/5/2020	4,618	121	66	0.4248
19/5/2020	4,853	125	72	0.4205
20/5/2020	5,271	142	78	0.4120
21/5/2020	5,542	138	84	0.4121
22/5/2020	5,948	–	90	0.3986
23/5/2020	6,248	–	95	0.4330
24/5/2020	6,638	–	104	0.5137
25/5/2020	6,930	–	114	0.4214
26/5/2020	7,210	–	124	0.4111
27/5/2020	7,761	–	133	0.4054
28/5/2020	8,300	–	142	0.4084
29/5/2020	8,722	–	154	0.3922
30/5/2020	9,474	–	162	0.4228
31/5/2020	9,780	–	170	0.4950
1/6/2020	10,510	–	171	0.4085
2/6/2020	11,256	–	177	0.4040
3/6/2020	11,398	–	181	0.3948
4/6/2020	12,923	–	196	0.3875
5/6/2020	14,208	–	202	0.3884
6/6/2020	15,850	–	208	0.3983
7/6/2020	16,623	–	214	0.4769
8/6/2020	16,948	–	226	0.3927
9/6/2020	18,090	–	236	0.3828
10/6/2020	19,433	–	256	0.3936
11/6/2020	20,507	–	274	0.4451
12/6/2020	21,396	–	282	0.3727
13/6/2020	21,959	–	293	0.4054
14/6/2020	22,871	–	304	0.4830
15/6/2020	23,684	–	319	0.3953
16/6/2020	25,379	–	348	0.4051
17/6/2020	27,140	–	365	0.3875
18/6/2020	28,521	–	379	0.3966

to be continue

continuation

Date	Cumulative cases	ICU <sup>a</sup> hospitalizations	Cumulative deaths	Percentage isolation
19/6/2020	30,902	–	396	0.3562
20/6/2020	32,238	–	405	0.4042
21/6/2020	33,227	–	423	0.4839
22/6/2020	34,148	–	449	0.4039
23/6/2020	35,368	–	475	0.3969
24/6/2020	37,254	–	495	0.3932
25/6/2020	38,871	–	509	0.3940
26/6/2020	41,326	–	532	0.3811
27/6/2020	42,766	–	537	0.4190
28/6/2020	44,905	–	548	0.4926
29/6/2020	47,071	–	559	0.4216
30/6/2020	49,218	–	587	0.4100
1/7/2020	50,676	–	620	0.4020
2/7/2020	52,281	–	631	0.4040
3/7/2020	53,996	–	643	0.3850
4/7/2020	55,760	–	671	0.4090
5/7/2020	57,854	–	699	0.4820
6/7/2020	60,383	–	726	0.4130
7/7/2020	62,694	–	767	0.3950
8/7/2020	64,314	–	801	0.3900
9/7/2020	65,677	–	823	0.4000
10/7/2020	67,297	–	856	0.3920
11/7/2020	68,406	–	871	0.4180
12/7/2020	70,712	–	902	0.4870
13/7/2020	72,284	–	930	0.4130
14/7/2020	73,654	–	960	0.4130
15/7/2020	75,379	–	1,001	0.4020
16/7/2020	77,621	–	1,037	0.4030
17/7/2020	79,400	–	1,060	0.3570
18/7/2020	81,163	–	1,075	0.3940
19/7/2020	82,412	–	1,085	0.4850
20/7/2020	84,287	–	1,112	0.4080
21/7/2020	86,076	–	1,158	0.4070
22/7/2020	87,801	–	1,176	0.3960
23/7/2020	90,023	–	1,218	0.3960
24/7/2020	92,414	–	1,244	0.3880
25/7/2020	94,187	–	1,275	0.4110
26/7/2020	96,332	–	1,308	0.4810
27/7/2020	98,480	–	1,339	0.4070
28/7/2020	100,726	–	1,391	0.4000
29/7/2020	102,342	–	1,419	0.3970
30/7/2020	104,442	–	1,444	0.3970
31/7/2020	106,292	–	1,469	0.3860

a) ICU: intensive care unit – data available as at 21/5/2020.

Sources: local Epidemiological Bulletins and the Inloco public database.<sup>11</sup>

### Supplementary Material 4 – Illustration of the probability distribution functions of the model's main parameters

