MOBILITY RESTRICTIONS FOR THE CONTROL OF COVID-19 EPIDEMIC

Bráulio Roberto Gonçalves Marinho Couto[1] - ORCID: 0000-0002-5314-5161

Joaquim José da Cunha Junior[2] - ORCID: 0000-0002-5083-9600

Cristóvão de Deus Martins Oliveira[3] - ORCID: 0000-0001-6229-4938

Gregory Lauar e Souza[3] - ORCID: 0000-0003-1525-5412

Handerson Dias Duarte de Carvalho[3] - ORCID: 0000-0002-3685-8936

Rhayssa Fernanda Andrade Rocha[3] - ORCID: 0000-0002-0557-8472

André Luiz Alvim[4] - ORCID: 0000-0001-6119-6762

Carlos Ernesto Ferreira Starling[5] - ORCID: 0000-0002-0446-6962

[1]Doctoral Degree in Bioinformatics, Centro Universitário de Belo Horizonte – Belo Horizonte (MG), Brazil.

[2]Doctoral Degree in Production Engineering, Centro Universitário de Belo Horizonte – Belo Horizonte (MG), Brazil.

[3]Medical student, Centro Universitário de Belo Horizonte – Belo Horizonte (MG), Brazil.

[4]Master's Degree. Nursing School, Universidade Federal de Minas Gerais – Belo Horizonte (MG), Brazil.

[5]Master's Degree in Medicine, Lifecenter Hospital – Belo Horizonte (MG), Brazil.

Corresponding author:

Bráulio Roberto Gonçalves Marinho Couto – Centro Universitário de Belo Horizonte – Rua Pedro Natalício de Moraes, 223, ap. 201 – Buritis – CEP: 30575-275 – Belo Horizonte (MG), Brazil – E-mail: brauliocouto@biobytebrasil.com

ABSTRACT

Objective: To determine whether the SEIR model, associated to mobility changes parameters, can determine the likelihood of establishing control over an epidemic in a city, state or country.

Study design and setting: The critical step in the prediction of COVID-19 by a SEIR model are the values of the basic reproduction number (R_0) and the infectious period, in days. R_0 and the infectious periods were calculated by mathematical constrained optimization, and used to determine the numerically minimum SEIR model errors in a country, based on COVID-19 data until April 11th. The Community Mobility Reports from Google Maps (<https://www.google.com/covid19/mobility>) provided mobility changes on April 5th compared to the baseline (Jan 3rd to Feb 6th). The data was used to measure the non-pharmacological intervention adherence. The impact of each mobility component was calculated by logistic regression models. COVID-19 control was defined by SEIR model $R_0<1.0$ in a country.

Results: The ECDC has registered 1,653,204 COVID-19 worldwide on April 11th. Sixteen countries presented 78% of all cases. Of the six Google Maps mobility parameters, the "Stay at home" parameter was the strongest one to control COVID-19 in a country: an increase of 50% in mobility trends for places of residence has a 99% chance of outbreak control.

Conclusions: Residential mobility restriction presented itself as the most effective measure. The SEIR model associated with mobility parameters proved to be a useful tool in determining the chance of COVID-19 outbreak control.

KEYWORDS: coronavirus infections; agent based modeling; 2019-nCoV pandemic; prevention and control; social distance.

INTRODUCTION

In December 2009, a cluster of patients with pneumonia was reported in the city of Wuhan, capital of Hubei province, China, caused by a novel coronavirus, named severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). This name was attributed to the virus due to its genetic relation to another coronavirus, responsible for the severe acute respiratory syndrome (SARS) outbreak of 2003[1,2]. In February 2020, the World Health Organization (WHO) announced COVID-19 as the name of this new disease[2]. On January 30th, 2020, the WHO declared that the outbreak of the new coronavirus (formerly called 2019-nCoV) constituted a Public Health Emergency of International Concern (PHEIC), advising countries to prepare for containment measures[3]. On March 11th, 2020, the WHO characterized COVID-19 as a pandemic[4].

Viral transmission is not fully understood yet. The spread of SARS-CoV-2 from person-to-person, via respiratory droplets, is the predominant hypothesis[5]. Individuals with asymptomatic infections or within the incubation period are also believed to transmit the virus[6,7].

Non-pharmacological interventions for the prevention of transmission and infection of this pathogen include isolation at home, voluntary quarantine at home, social distancing from the entire population, especially the elderly, and temporary closure of schools, universities, and workplaces[8].

Mathematical models can provide a better understanding of the transmission dynamics of COVID-19. Using a well-fitted mathematical model, it is possible to extrapolate current information about the epidemic, to estimate the chances for future outbreak control, and to provide guidance for the creation of mitigation strategies by public health agents.

The modeling of infectious diseases can be done by compartmental mathematical models such as SIR (susceptible-infected-recovered), SEIR (susceptible-exposed-infected-recovered), SIS (susceptible-infected-susceptible), MSIR (maternally derived immunity-susceptible-infected-recovered)[9]. The objective of the study was to evaluate whether the SEIR model, associated with different community mobility restriction parameters, can determine the chances of controlling COVID-19 outbreaks.

METHODS

The susceptible-exposed-infected-recovered (SEIR) compartmentalized epidemiological model has been previously used during the initial wave of the H1N1 influenza pandemic in 2009. A susceptible person (S) is exposed to the virus and becomes a latent or exposed individual (E). After the incubation period, latent individuals become infected (I), who can be recovered (R) in a specific period of time by a recovery rate (dead people are included in the recovered group). Increased transmission and recovery rates ultimately abbreviate the total duration of the epidemic[10].

The SEIR model is defined by a system of four ordinary differential equations, which are described in the algorithm (Figures 1A and 1B). For the mathematical modeling of the spread of COVID-19, four parameters of the SEIR model were obtained by international experiences: the incubation period=3.7 days[11], the proportion of critical cases=0.05[11], the overall case-fatality rate=0.023[11], and the estimated proportion of asymptomatic patients with COVID-19=0.18[12]. These values can be modified for a specific region, but, the critical step in the prediction of COVID-19 by the model is the value of the basic reproduction number (R_0) and the infectious period, in days (T_infectious), which were calculated by mathematical constrained optimization.

```
Algorithm COVID
    Read N {population's size}
    Read T_phase_I {duration of the first phase of the epidemic (days)}
    Read = R0_phase_I {basic reproduction number for COVID-19 from the first phase of the epidemic}
    Read T_infectious_phase_I {the infectious period from the first phase of the epidemic (days)}
    Read T_phase_II {duration of the second phase of the epidemic (days)}
    Read = R0_phase_II {basic reproduction number for COVID-19 from the second phase of the epidemic}
    Read T_infectious_phase_II {the infectious period from the second phase of the epidemic (days)}
    Read = R0_phase_III {basic reproduction number for COVID-19 from the third phase of the epidemic}
    Read T_infectious_phase_III {the infectious period from the thrid phase of the epidemic (days)}
    T_incubacao = 3.7 {COVID-19 the incubation period, in days}
    p_CTI = 0.05 {spectrum of disease: proportion of critical COVID-19 cases}
    letalidade = 0.023 {the overall case-fatality rate}
    p_assintomaticos = 0.18 {asymptomatic proportion of COVID-19}
    f = 1/T_incubacao {the rate at which individuals move from the latent class to the infected class}
    t = 0 {first day = "zero day"}
    t_Max = 180 {last day of simulation: 180 days after the first COVID-19 case}
    Susceptivel[t] = (N - COVID) {susceptible individuals}
    Preinfec[t] = 0 {exposed or latent patients}
    COVID[t] = 1 {infected patients or COVID-19 cases}
    Imunes[t] = 0 {recovered or immune patients}
    CTI[t] = 0 {critical cases}
    Obitos[t] = 0 {case-fatality}
...
```

A

```
...
Repeat
    t = t + 1
    If (t ≤ T_phase_I)then
                    ecr = R0_phase_I/T_infectious_phase_I {effective contact rate for phase 1}
                    recupera = 1/T_infectious_pahse_I {recovery rate for phase 1}
                else Se (t ≤ T_phase_II)then
                    ecr = R0_phase_II/T_infectious_phase_II {effective contact rate for phase 2}
                    recupera = 1/T_infectious_pahse_II {recovery rate for phase 2}
                else
                    ecr = R0_phase_III/T_infectious_phase_III {contact rate for phase 3}
                    recupera = 1/T_infectious_pahse_III {recovery rate for phase 3}
    End If

    Beta = ecr/N {transmission rate}
    Susceptivel[t] = Susceptivel[t-1] - Beta*COVID[t-1]*Susceptivel[t-1]
    Preinfec[t] = Preinfec[t-1] + Beta*COVID[t-1]*Susceptivel[t-1]-f*Preinfec[t-1]
    COVID[t] = COVID[t-1] + f*Preinfec[t-1] - recupera*COVID[t-1]
    Imunes[t] = Imuntes[t-1] + recupera*COVID[t-1]
    CTI[t] = p_CTI*COVID[t]
    Obitos[t] = letalidade*Imunes[t]*p_assintomaticos
    Write t, Susceptivel[t],Preinfec[t],COVID[t],Imunes[t],CTI[t],OBitos[t]
    If (t = t_Max)
        Then break
    End If
End Repeat
End Algorithm
```

B

SEIR: susceptible-exposed-infected-recovered.

Figure 1 – Algorithm for the SEIR model applied to COVID-19: (A) initialization; (B) calculation of new COVID-19 cases day-by-day.

A Solver from Microsoft® Excel or NEOS Server, for example (https://neos-server.org/neos/), can be used for finding numerically minimum of a function Z, which represents the sum of squared errors between each new case of COVID-19 observed in one day, and the cases predicted by the SEIR model in three phases (Equation 1):

$$Minimize\ Z = \sum_{i=1}^{D} (I_i - \hat{I}_i)^2 \quad (1)$$

Subject to

$$\begin{cases} T\_phase\_I \leq D \\ 0.5 \leq R0\_phase\_I \leq 20 \\ 2 \leq T\_infectious\_phase\_I \leq 14 \\ T\_phase\_II \leq T\_phase\_I \\ 0.5 \leq R0\_phase\_II \leq 20 \\ 2 \leq T\_infectious\_phase\_II \leq 14 \\ 0.5 \leq R0\_phase\_III \leq 20 \\ 2 \leq T\_infectious\_phase\_III \leq 14 \end{cases}$$

In which:

I_i = number of COVID-19 new cases observed in a city, state or country during the day i;

$\hat{I}_i$ = number of COVID-19 new cases predicted by the model in the day i;

D = total days of the epidemic in a city, state or country;

T_phase_I = duration of the first phase of the epidemic (days);

R0_phase_I = basic reproduction number for COVID-19 from the first phase of the epidemic;

T_infectious_phase_I = infectious period from the first phase of the epidemic (days);

T_phase_II = duration of the second phase of the epidemic (days);

R0_phase_II = basic reproduction number for COVID-19 from the second phase of the epidemic;

T_infectious_phase_II = infectious period from the second phase of the epidemic (days);

R0_phase_III = basic reproduction number for COVID-19 from the third phase of the epidemic;

T_infectious_phase_III = infectious period from the third phase of the epidemic (days).

In Equation 1, values of the number of COVID-19 new cases predicted by the day-by-day ($\hat{I}_i$,) model are calculated for a specific country by using the algorithm for the SEIR model applied to COVID-19 (Figures 1A and 1B). A video (available in Portuguese only) with an explanation about the COVID-19 SEIR modeling in Microsoft® Excel, in addition to a spreadsheet are available at: <https://www.dropbox.com/sh/28db9ljm1uoppdq/AADOfqLRqoDj6JO0qpF4zAHSa?dl=0>.

The Community Mobility Reports from Google Maps aim to provide insights into what has changed in response to policies aimed at combating COVID-19 (<https://www.google.com/covid19/mobility/>). The reports chart movement trends over time by geographic regions, across different categories of places such as retail and recreation, groceries and pharmacies, parks, transit stations, workplaces, and residential. This data is retrieved from users mobile phone location tracking, obtained with previous user consent. The Mobility Report from Google Maps was used to measure adherence to non-pharmacological intervention (Google LLC "Google COVID-19 Community Mobility Reports").

The impact of each mobility component was caused by logistic regression models, and the outcome control in a country is defined by a basic reproduction number (R0) below 1.0.

Six logistic regression models were built for each Google Maps mobility parameter: Retail & recreation (mobility trends for places like restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters); Grocery and pharmacy (mobility trends for places like grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies); Parks (mobility trends for places like national parks, public beaches, marinas, dog parks, plazas, and public gardens); Transit stations (mobility trends for places like public transport hubs such as subway, bus, and train stations); Workplaces (mobility trends for places of work); and Residential (mobility trends for places of residence). The percentage of mobility changes in each country was the exposure variable for the logistic regression modeling.

RESULTS

On April 11th, the European Centre for Disease Prevention and Control (ECDC) registered 1,653,204 COVID-19 cases (<https://www.ecdc.europa.eu/en/publications-data/download-todays-data-geographic-distribution-covid-19-cases-worldwide>) from 206 countries and territories, of which only 16 (8%) accounted for 78% of all cases (Figure 2).

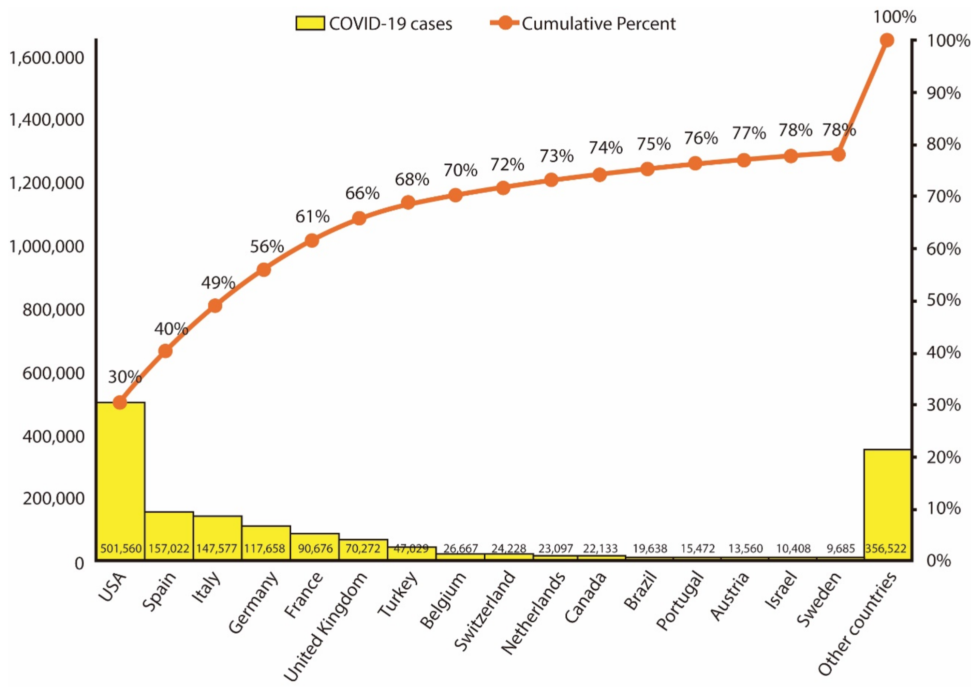
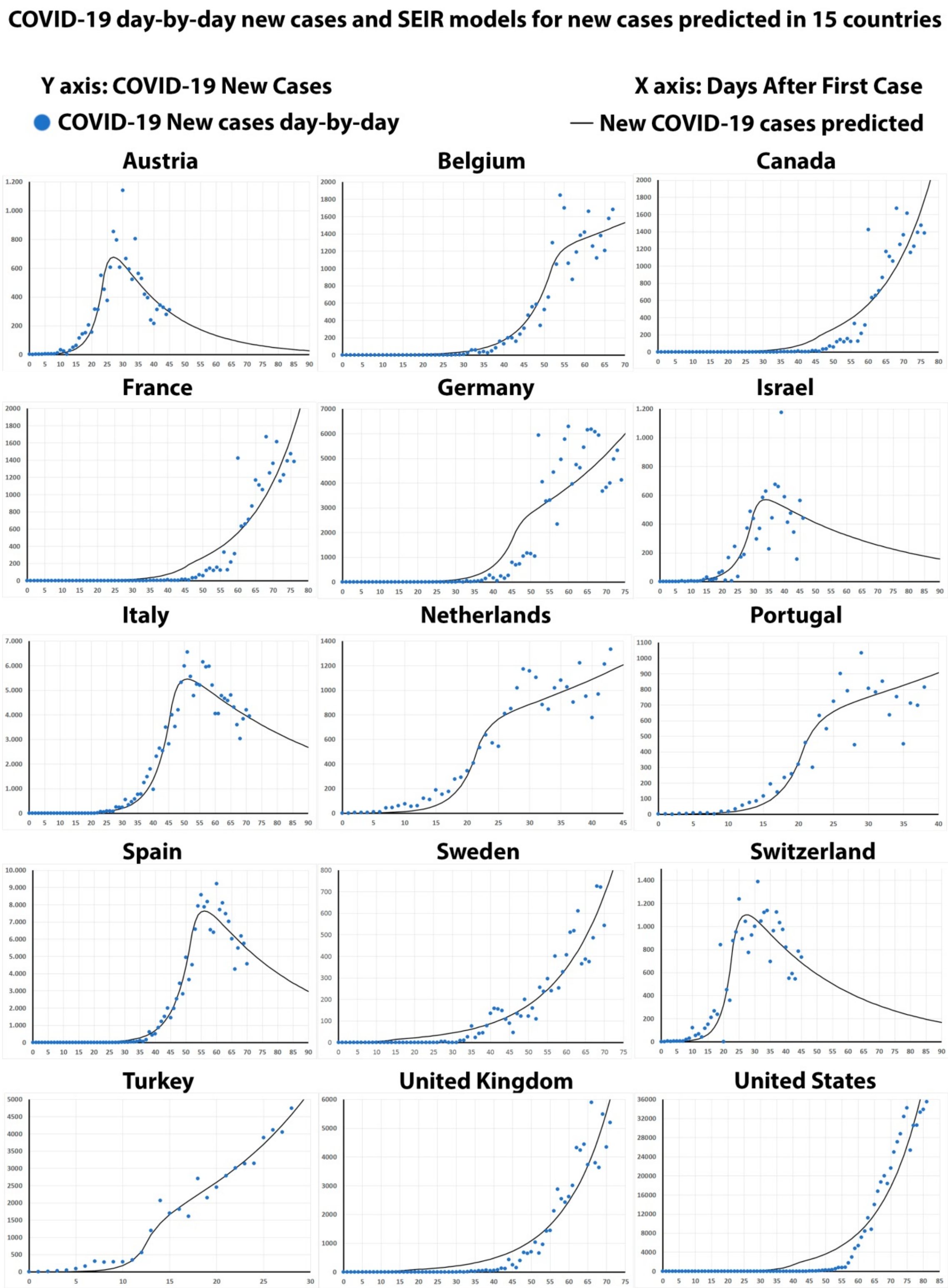


Figure 2 – Pareto distribution of COVID-19 cases on April 11th, 2020.

Table 1 shows the changes in mobility on April 5th compared to the baseline (5-week period; Jan 3rd to Feb 6th, 2020) and the numbers of reproduction (R_0) and infectious periods, in days (T_infectious), for these 16 countries. Only Spain, Austria, Switzerland, Italy, and Israel had R_0 less than 1.0, i.e., only five countries had controlled the epidemic on April 5th. Figure 3 shows the SEIR models the countries.



SEIR: susceptible-exposed-infected-recovered.

Figure 3 – SEIR models: R_0 and T_infectious are values that minimize the model error in predicting new COVID-19 cases day-by-day.

Table 1. The Community Mobility Reports from Google Maps: Mobility changes on April 5th compared to the baseline (5-week period; Jan 3rd–Feb 6th, 2020): T_infectious and R_0 obtained by using COVID-19 new cases day-by-day in each country, adjusted to the SEIR model by mathematical constrained optimization.

Country	Cases on April 11th	Days after first cases	Mobility changes on April 5th compared to the baseline (5-week period; Jan 3rd–Feb 6th, 2020)							T_infectious (days)	R_0
			Population (2018)	Retail & recreation	Grocery & pharmacy	Parks	Transit stations	Workplaces	Residential		
Spain	157,022	71	46,723,749	-94%	-77%	-90%	-89%	-68%	23%	14.0	0.5
Austria	13,560	46	8,847,037	-82%	-55%	-11%	-64%	-46%	12%	7.3	0.5
Switzerland	24,228	46	8,516,543	-76%	-25%	42%	-48%	-42%	12%	10.4	0.6
Italy	147,577	72	60,431,283	-95%	-82%	-90%	-86%	-62%	24%	14.0	0.7
Israel	10,408	47	8,883,800	-75%	6%	-52%	-57%	-60%	30%	8.2	0.7
Belgium	26,667	68	11,422,068	-76%	-36%	-13%	-60%	-46%	15%	8.7	1.2
Netherlands	23,097	44	17,231,017	-54%	-16%	41%	-52%	-29%	8%	7.0	1.2
France	90,676	78	66,987,244	-85%	-62%	-73%	-82%	-53%	17%	13.9	1.2
Portugal	15,472	40	10,281,762	-84%	-60%	-88%	-82%	-55%	23%	11.6	1.3
Germany	117,658	75	82,927,922	-58%	-13%	61%	-47%	-30%	8%	14.0	1.6
UK	70,272	72	66,488,991	-82%	-41%	-29%	-70%	-54%	15%	6.3	2.0
Sweden	9,685	71	10,183,175	-25%	-9%	69%	-37%	-18%	6%	14.0	2.5
Turkey	47,029	29	82,319,724	-76%	-40%	-61%	-76%	-48%	19%	13.3	2.5
USA	501,560	82	327,167,434	-49%	-20%	-20%	-54%	-40%	13%	8.8	2.3
Canada	22,133	77	37,058,856	-63%	-45%	-13%	-67%	-46%	14%	14.0	2.6
Brazil	19,638	43	209,469,333	-67%	-24%	-66%	-57%	-30%	15%	9.3	2.6

UK: United Kingdom; USA: United States of America.

The basic numbers of reproduction (R_0) and infectious periods, in days (T_infectious), in Table 1 were calculated for the third phase of the epidemic by the mathematical constrained optimization used to find the numerically minimum of a Z function (Equation 1) in each country, based on real COVID-19 data until April 11th. These numbers represent every new cases, meaning that $R_0<1$ represent a controlled scenario, and values higher than one stand for an uncontrolled one, that is, the higher the figure the more the infection is spread.

Table 2 summarizes the impact of each mobility component on epidemic control. The chance of control is calculated by logistic regression models. The logistic regression used logistic coefficients for each of the 6 parameters based on Google Maps® localization data. These logistic coefficients were then used to calculate the minimum mobility restrictions for each parameter and also the chance to control the outbreak in case such restriction percentages were met.

Table 2. Logistic regression models to evaluate the chance of an epidemic control based on the non-pharmacological interventions adherence.

Mobility changes parameter		Logistic regression unstandardized coefficients		Minimum mobility restrictions for COVID-19 control	
		Constant	**Logistic coefficient**	**Percentage (%)**	**Chance of outbreak control (%)**
Retail & recreation	Mobility trends for places like restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters.	-11.127	-13.4	-100	91
Grocery & pharmacy	Mobility trends for places like grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies.	-1.720	-2.3	-100	64
Parks	Mobility trends for places like national parks, public beaches, marinas, dog parks, plazas, and public gardens.	-1.048	-0.9	-100	46
Transit stations	Mobility trends for places like public transport hubs such as subway, bus, and train stations.	-2.774	-3.0	-100	56
Workplaces	Mobility trends for places of work.	-7.258	-13.2	-72	90

Residential	Mobility trends for places of residence.	-3.779	17.7	+34	90

Residential mobility restriction presented the highest logistic coefficient (17.7), *i.e.*, this parameter had a high impact on outbreak control, considering that a 32% increase in the isolation of people in their households can generate a 90% chance of controlling the outbreak.

Workplace mobility restriction was the second most effective measure, considering a minimum restriction of 56% for an outbreak control chance of 53%. Retail and recreation mobility presented 53 and 86%, respectively. Transit stations (96 and 54%) were also assessed. Park mobility restriction demonstrated the least efficacy in outbreak control, considering that absolute restriction (100%) provided the lowest chance of outbreak control (46%).

The impact of each Google Maps mobility component on the probability of epidemic control was simulated in Figure 4: “stay at home” and “stay out of the workplace” are the strongest ways to control COVID-19 spreading. Based on these simulations in the graph, it is possible to evaluate the impact of each mobility component. For example, to achieve at least a 50% chance of epidemic control, it is necessary an increase of only 22% in the mobility trends for places of residence. On the other hand, a reduction in all other components is necessary to a successful control of the epidemic: 56% cutback in the mobility trends for places of work; minus 84% in places like restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters; minus 76% in places like grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies; minus 92% in places like public transport hubs such as subway, bus, and train stations. Even a 100% reduction in the mobility trends for places like national parks, public beaches, marinas, dog parks, plazas, and public gardens it is not enough to control the COVID-19.

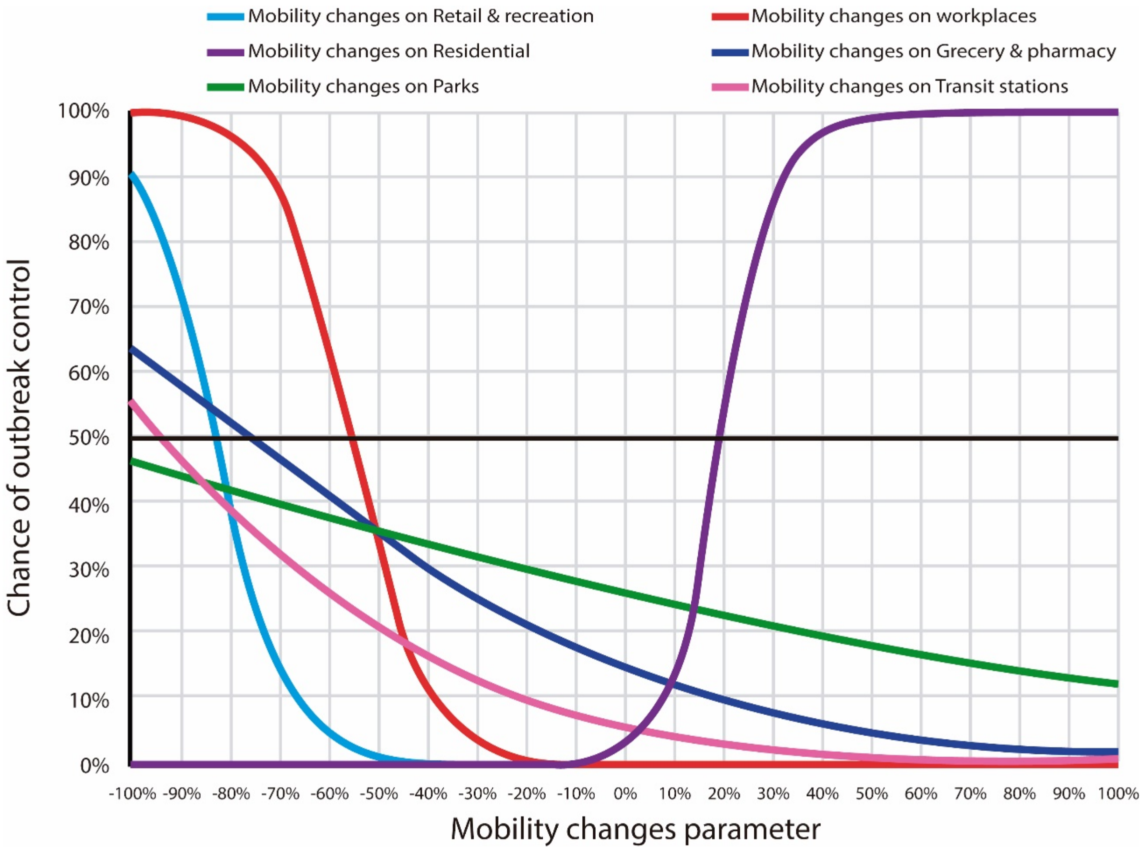


Figure 4 – Simulation of the impact of the mobility component in the chance of outbreak control: analysis by using the logistic regression model summarized in Table 2.

DISCUSSION

This study is based on a mathematical modeling which, in spite of being subject to limitations, can foretell COVID-19 cases in a region. The analysis was not performed by a statistical modeling process, but rather by a numerical perspective. The reproduction number of COVID-19 was estimated according to the cases confirmed and registered in each country. Although R_0 was higher than initially expected, estimates based on likelihood and model analysis have shown that R_0 could be as high as 6.5[13]. These higher values are compatible with other studies, such as Liu et al., which concluded that the reproductive number of COVID-19 is higher than that of SARS coronavirus[14].

Analyzing R_0 values, it is possible to measure the spread or control of the epidemic in each country. Table 1 shows that of the 16 countries analyzed, only 5 show $R_0<1$, which represents a controlled epidemic. These 5 countries had mean R_0 of 0.6 and the biggest change in Residential mobility in the period. The remaining 11 countries had mean R_0 of 1.9. There was a raise in 20% of the population at home compared to the baseline in these 5 countries on April 5th, whereas the other 11 countries had a 14% increase. This indicates the correlation between the change in populational Residential mobility and the control of the epidemic.

A 50% rate of social isolation at home is estimated to be considered sufficient to control COVID-19 epidemic. Residential mobility restriction presented itself as the most effective measure for the least amount of effort, considering an increase of 50% in the mobility trends for places of residence has a 99% chance of outbreak control. It is speculated that residency isolation would indirectly reduce the total number of individuals in public places.

The degree to which mobility restrictions increase or decrease the overall epidemic size depends on the level of risk in each community and the characteristics of the disease[15]. More research is required in order to estimate the optimal balance between mobility restriction, outbreak control, economy, and freedom of movement.

CONFLICT OF INTERESTS

The authors declare no conflict of interests.

AUTHORS' CONTRIBUTIONS

Study conception, study design and data acquisition: Starling CEF, Junior JJC, Couto BRGM, Oliveira CDM, Souza GL, Carvalho HDD, Rocha RFA, Alvim AL. Statistical analysis: Couto BRGM.

REFERENCES

1. Zhu N, Zhang D, Wang W, Li X, Yang B, Song J, et al. A Novel Coronavirus from Patients with Pneumonia in China, 2019. N Engl J Med. 2020;382:727-33. http://doi.org/10.1056/nejmoa2001017
2. Wang Y, Wang Y, Chen Y, Qin Q. Unique epidemiological and clinical features of the emerging 2019 novel coronavirus pneumonia (COVID-19) implicate special control measures. J Med Virol. 2020;92(6):568-76. http://doi.org/10.1002/jmv.25748
3. World Health Organization. Statement on the meeting of the International Health Regulations (2005) Emergency Committee regarding the outbreak of novel coronavirus (2019-nCoV). WHO; 2020.
4. World Health Organization. WHO Director-General's opening remarks at the mission briefing on COVID-19 [Internet]. WHO; 2020 [accessed on Mar 11, 2020]. Available at: https://www.who.int/dg/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19---11-march-2020
5. Chan JFW, Yuan S, Kok KH, To KK-W, Chu H, Yang J, et al. A familial cluster of pneumonia associated with the 2019 novel coronavirus indicating person-to-person transmission: a study of a family cluster. Lancet. 2020;395:514-23.

http://doi.org/10.1016/S0140-6736(20)30154-9

6. Bai Y, Yao L, Wei T, Tian F, Jin D-Y, Chen L, et al. Presumed Asymptomatic Carrier Transmission of COVID-19. JAMA. 2020;323(14):1406-7. http://doi.org/10.1001/jama.2020.2565

7. Yu P, Zhu J, Zhang Z, Han Y, Huang L. A familial cluster of infection associated with the 2019 novel coronavirus indicating potential person-to-person transmission during the incubation period. J Infect Dis. 2020;221(11):1757-61. http://doi.org/10.1093/infdis/jiaa077

8. Agrawal S, Goel AD, Gupta N. Emerging prophylaxis strategies against COVID-19. Monaldi Arch Chest Dis. 2020;90(1). http://doi.org/10.4081/monaldi.2020.1289

9. Radcliffe J, Bailey NTJ. The Mathematical Theory of Infectious Diseases and its Applications. 2ª ed. J Royal Statist Soc Appl Stat. 1977;26(1):85-7. http://doi.org/10.2307/2346882

10. Ridenhour B, Kowalik JM, Shay DK. Unraveling R0: Considerations for public health applications. Am J Public Health. 2014;104(2):e32-41. http://doi.org/10.2105/AJPH.2013.301704

11. Wu Z, McGoogan JM. Characteristics of and Important Lessons From the Coronavirus Disease 2019 (COVID-19) Outbreak in China. JAMA. 2020;323(13):1239-42. http://dx.doi.org/10.1001/jama.2020.2648

12. Mizumoto, K, Kagaya, K, Zarebski A, Chowell G. Estimating the asymptomatic proportion of coronavirus disease 2019 (COVID-19) cases on board the Diamond Princess cruise ship, Yokohama, Japan, 2020. Euro Surveill. 2020;25(10). http://dx.doi.org/10.2807/1560-7917.ES.2020.25.10.2000180

13. Shen M, Peng Z, Xiao Y, Zhang L. Modelling the epidemic trend of the 2019 novel

coronavirus outbreak in China. bioRxiv. 2020. http://dx.doi.org/10.1101/2020.01.23.916726

14. Liu Y, Gayle AA, Wilder-Smith A, Rocklöv J. The reproductive number of COVID-19 is higher compared to SARS coronavirus. J Travel Med. 2020;27(2). http://dx.doi.org/10.1093/jtm/taaa021

15. Espinoza B, Castillo-Chavez C, Perrings C. Mobility Restrictions for the Control of Epidemics: when do they work? SSRN. 2019. http://dx.doi.org/10.2139/ssrn.3496928