Supplementary Materials

The structure of Materials and Methods is as follows: we first introduce the construction process of our model-specific database in the "Datasets" section. Then, in the "Model" section, the origin of final parameter interval for different classes is explained. Finally, in the "Classification and forecast method" section, the detailed procedure for classifying the observed curve of daily reported cases and predicting the development is presented.

Datasets

Storage of epidemic COVID-19 curve

From the dataset of World Health Organization (*1*) and Our World in Data (*2*), we collected and saved the daily new cases of COVID-19 covering the data from January 22, 2020 to April 9, 2021 from more than 60 countries and regions. The date is accurate to the day, however, due to different conditions, statistical methods and administrative implementation between countries, the data vary greatly in form and in scale. In our study, these data were presented in form of curves by setting date as horizontal axis and the number of daily new cases as vertical axis.

Process of epidemic COVID-19 curve

In order to facilitate the extraction and the analysis of features of the original data, a preliminary process was introduced. The pre-processing contained two steps. The first step was smoothing the data. The number of each day was smoothed by the data of seven days before and after, which means we replaced the number of that day by the average value of the seven days. This procedure can partly remove the noise in the data and help reflect the trend. Secondly, we divided the data of each country/region into a minor level: waves. Each wave represents a round of outbreak and mitigation of COVID-19. The following rule were used to identify a wave: it starts from the closest

SUPPLEMENTARY TABLE S1. Classification of different non-pharmaceutical interventions of history wave and their forecast parameter $t_{30\%}$.

Non-pharmaceutical interventions	Country/Region	Period	Classification	$t_{30\%}$	Average $t_{30\%}$
	France	2020.8–2020.12	A	23	
	South Africa	2020.9–2021.3	A	12	
Lockdown	Belgium	2020.8–2020.12	A	14	23
	Austria	2020.8–2021.1	A–	33	
	UK	2020.9–2021.3	B	32	
	The Republic of Korea *	2020.2– 2020.4	A	12	
	Hong Kong *	2020.3– 2020.5	A–	16	/
	Japan *	2020.1– 2020.3	B	22	
Mask wearing	Japan	2020.9–2021.1	B	24	
	The Republic of Korea	2020.10–2021.2	B–	33	30
	Spain	2020.7–2020.11	B–	32	
	Texas	2020.9–2021.3	B	34	
	Hungary	2020.8–2021.1	B–	44	
Social distancing + Curfew	Illinois	2020.9–2021.1	C	42	44
	Florida	2020.9–2021.2	C	35	
	Slovenia	2020.8–2021.3	C	63	
	Iowa	2020.9–2021.1	B–	32	
	New York	2020.9–2021.2	B–	57	
Social distancing	Germany	2020.8–2021.2	B–	44	48
	Switzerland	2020.8–2021.2	C	35	
	Sweden	2020.9–2021.2	C	70	

* The history waves were not counted into the average value of $t_{30\%}$.

inflection point before its augmentation and ends on the closest inflection point after its decline. The inflection point was defined as the points between two local maximums of the smoothed data around which the data remained stable. The following research will mainly focus on the waves of the smoothed data of all the sample countries.

Classification of epidemic curve in training set

We subdivided the original epidemic data into wave-based data and randomly divided them into a training set and a test set at a ratio of 8∶2. The training set was used to build the model, and the test set was used to test the validity of the model. We manually classified the epidemic wave curve in the training set into three levels: A, B, and C based on the pandemic control efficiency in previous text, part "Classification and forecast of the braking force effect" with level A being the highest and level C being the lowest (Supplementary Figure S1). Therefore, the database contained the classified training set and the test set to be verified. The data in both sets were based on the smoothed epidemic curve data of each wave in each sample country/region.

Model

Initial parameter intervals

To obtain the initial parameter interval of each Braking Force Effect Level, epidemic curves in training set were processed. Since the Gaussian function was frequently used to describe the natural phenomenon including the spread of infectious disease, while the epidemic curve usually has strong fluctuation, our study applied a linear combination of three Gaussian functions to fit the epidemic curve, which could be expressed as follow:

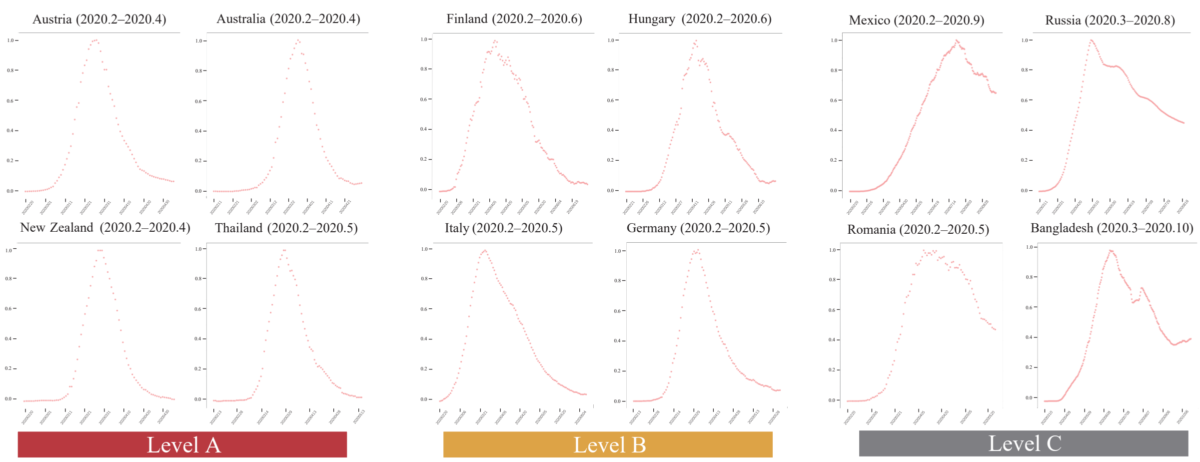
$$f(x) = a_1 \frac{e^{-(x-\mu_1)^2}}{2\sigma_1^2} + a_2 \frac{e^{-(x-\mu_2)^2}}{2\sigma_2^2} + a_3 \frac{e^{-(x-\mu_3)^2}}{2\sigma_3^2}$$

In which, a_i, μ_i, σ_i are the amplitudes, mean value and standard deviation of each Gaussian function. Loss function is defined as the mean-square error $\delta(X) = \sum_{i=1}^{n} \frac{(y_i - f(x_i))^2}{n}$ in which n is number of points in the origin epidemic curve, x_i and y_i are the abscissa and ordinate of the corresponding point.

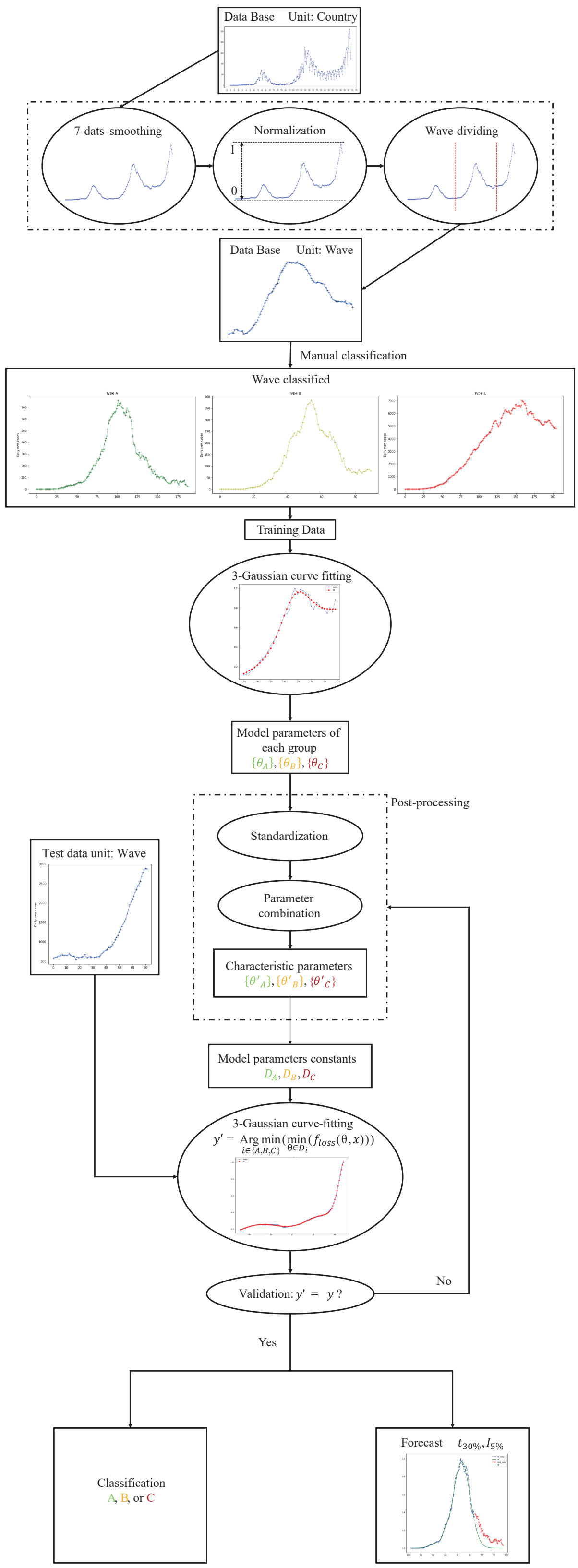
Since there were nine parameters to fit, an algorithm combining the Bayesian algorithm and gradient descent method was proposed to enhance the speed and accuracy, in which the Bayesian algorithm could quickly find a feasible solution close to the optimal solution in the search space and the gradient descent method was used to effectively approximate the optimal solution.

Through the above method, the epidemic wave in the training set could be quickly and accurately fitted by the linear combination of three Gaussian functions. After each fitting, it generated a set of data containing nine corresponding parameters, therefore the initial parameter intervals of each level were formed.

Final parameter intervals. Albeit the initial parameter had been found, the classification and forecast capability of the model was not satisfied. The reason was that the nine independent parameters intervals cannot effectively represent the three classes of epidemic curve. Therefore, feature parameters have been setup in order to reduce the

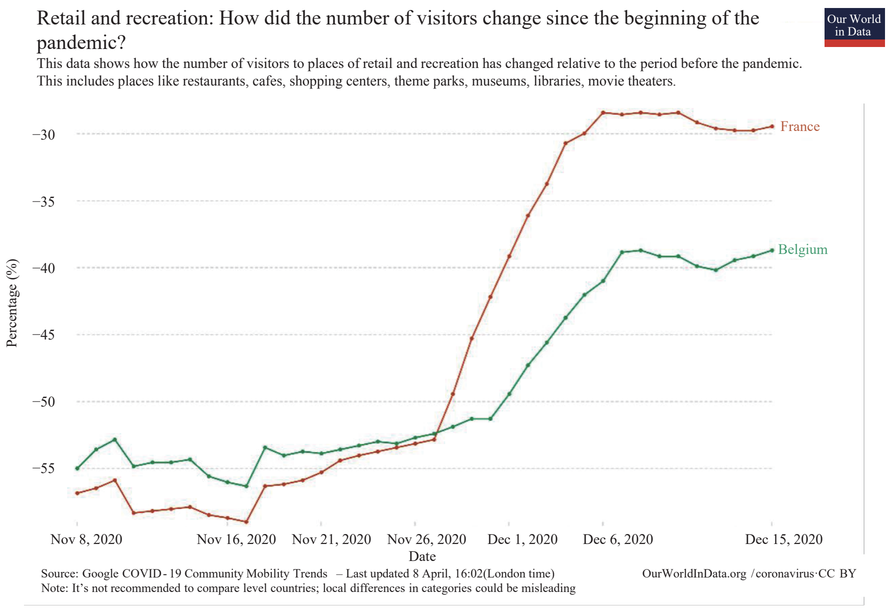


SUPPLEMENTARY FIGURE S1. Samples of pandemic wave classified into braking force effect level A, B, and C according to the pandemic control effectiveness.

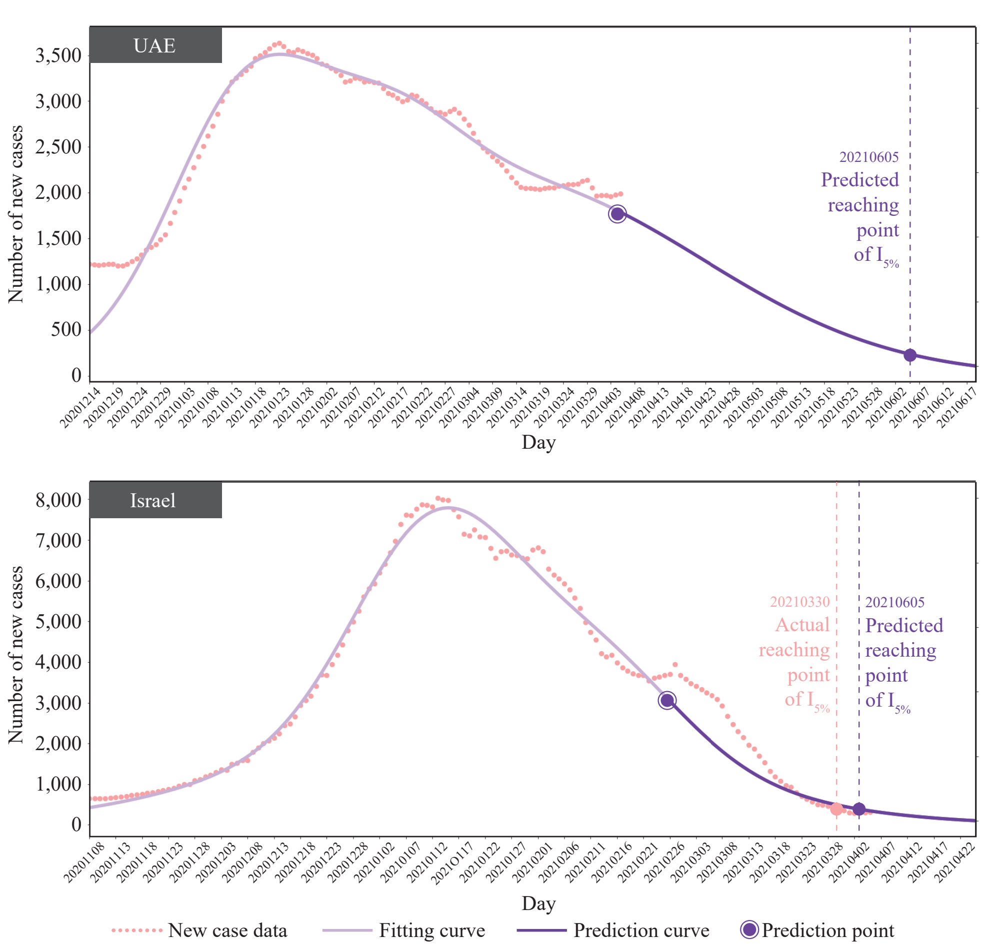


SUPPLEMENTARY FIGURE S2. Flow chart of classification and forecast with detail information of the Braking Force Effect model above the caption.

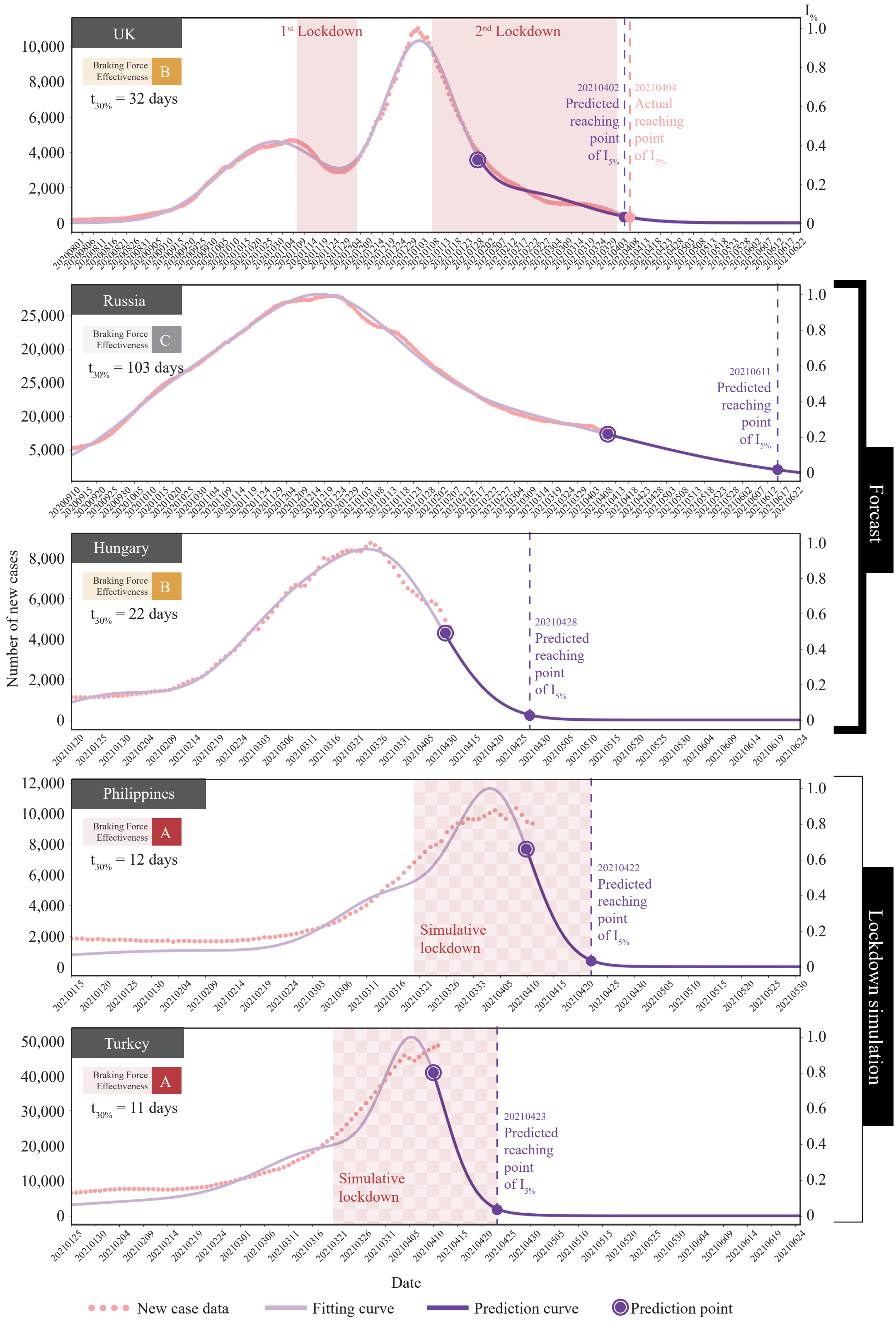
Note: I%: A parameter to predict the number of new daily cases as a percentage relative to the highest number of daily cases during the current wave of the pandemic.



SUPPLEMENTARY FIGURE S3. Community mobility trends of France and Belgium during the period of November 8 to December 15, 2020 (*1*).

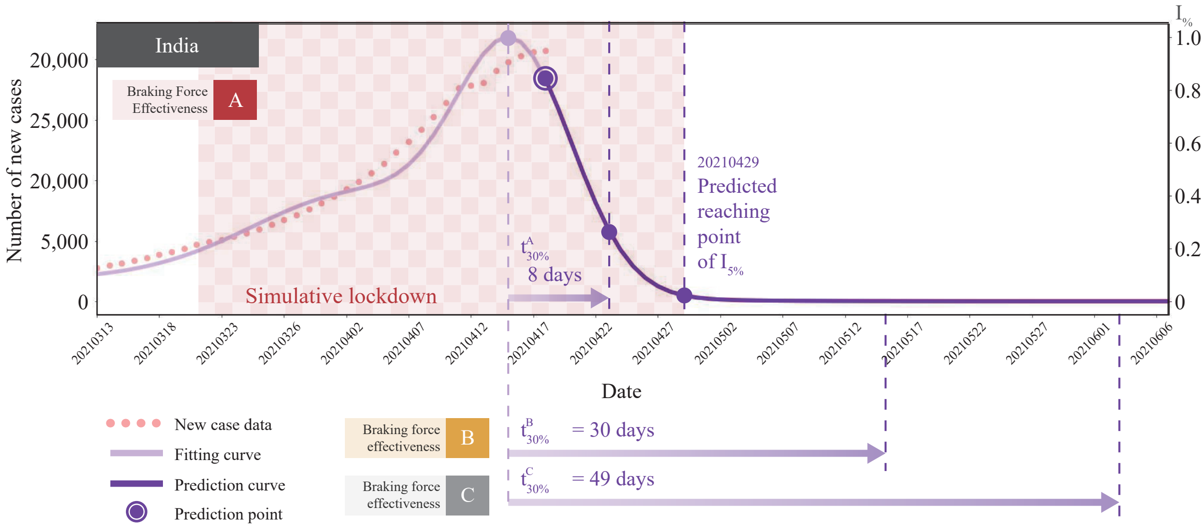


SUPPLEMENTARY FIGURE S4. Forecast of current pandemic wave of Israel and UAE.
Note: I%: A parameter to predict the number of new daily cases as a percentage relative to the highest number of daily cases during the current wave of the pandemic.



SUPPLEMENTARY FIGURE S5. "Braking Force Effect" model application. (A) "Braking Force Effect" model application to UK; (B) forecast of COVID-19 new case of Russia and Hungary. (C) "Braking force effect" model simulation of new case number tendency if The Philippines and Turkey implement Level A NPIs.

Note: I%: A parameter to predict the number of new daily cases as a percentage relative to the highest number of daily cases during the current wave of the pandemic.



SUPPLEMENTARY FIGURE S6. "Braking Force Effect" model simulation of new case number tendency for India with different Braking Force Effectiveness.
Note: I%: A parameter to predict the number of new daily cases as a percentage relative to the highest number of daily cases during the current wave of the pandemic.

initial parameter interval as well as to improve the classification and forecast capabilities of the model.

The feature parameters are a_1, a_{2_r}, a_{3_r}, μ_{1_n}, μ_{2_n}, μ_{3_n}, σ_{1_n}, σ_{2_r}, σ_{3_r}, where $a_{i_r} = {}^{a_i}\!/_{a_1}$, $i = 2, 3$; $\mu_{i_r} = {}^{a_i}\!/_{N}$, $i = 1, 2, 3$; $\sigma_{1_n} = {}^{\sigma_1}\!/_{N}$; $\sigma_{i_r} = {}^{\sigma_i}\!/_{\sigma_1}$, $i = 2, 3$ and N is the number of sampling points. The selection of index i is to evaluate the influence of the second and third peak to the main peak to estimate the fluctuation of the epidemic curve. The selection of index n is to limit the range of μ and σ when processing a long-term epidemic wave. Through the limitation of these new feature parameters, the final parameter intervals were calculated, and it was found that their range is greatly limited comparing to the initial parameter intervals. As a result, the overlap between each class in the nine-dimension space was reduced, the capability of classification was effectively improved.

Characteristic parameters

Besides the feature parameters used to calculate the final parameter interval mentioned above, characteristic parameters have been setup to assist the classification. The boxplot was used to exploit these parameters in order to distinguish the interval of each level. Characteristic parameters that meet the above requirement could be expressed below which were mainly related to a_1, a_2, a_3, σ_2, because these parameters would greatly influence the fluctuation of epidemic curve.

$$a_{sqr} = \frac{\sqrt{a_2^2 + a_3^2}}{a_1}, \quad a_{3_r} = \frac{a_3}{a_1}, \quad a_{23_r} = \frac{a_2 \times a_3}{a_1^2},$$
$$t_2 = a_{23_r} \times a_{2_r} \times \sigma_{2_r}, etc.$$

These characteristic parameters of epidemic wave in the training set of each level presented a certain interval, and the scatter chart between 2 characteristic parameters, e.g., a_{sqr} *Vs* a_{3_r} or a_{23_r} *Vs* t_2, presented a characteristic spatial distribution and slope range. By analyzing the characteristic parameters and the scatter charts, we can classify the types of one epidemic wave.

Classification and Forecast Method

Classification method

To classify the existing curve of each wave according to the criteria mentioned in the "Datasets" section, our standard procedure was divided into three steps. First, fit respectively the existing wave within the final parameter intervals of three levels obtained in the "Model adjustment" part by using the linear combination of three Gaussian functions. Second, classify preliminarily the waves by choosing the level with the smallest chi-squared value, if the chi-squared value was almost equally to two neighbor level, e.g. "A and B" and "B and C," the wave would be classified as A– and B–, respectively. Third, calculate the corresponding characteristic parameters and their relative scatter charts. By comparing the relative distance to other points of three levels and the slope from the position to the origin, the auxiliary result could be obtained to judge quantitatively whether the preliminary classification is reasonable. If the result between preliminary and auxiliary classification was the same then the former judgment would be accepted; otherwise, the wave would be reclassified. By repeating the classification until they were agreed, the final classification could be obtained, including A, A–, B, B–, C.

Forecast Method

To predict the number of daily reported cases, the nine parameters of the linear combination of three Gaussian function were firstly calculated according to the procedure in "Classification Method" part. The wave thus could be extended as the forecast result. The flow chart of classification and forecast with detail information of the "braking force effect" model is presented in Supplementary Figure S3.

During the forecast, a variable named $t_{30\%}$ was defined for indicating the decrease velocity of pandemic wave, unit of days, presented as the number of days required to decrease from the summit of wave to its 30%. We supposed a wave normalized as $w : [\![0, N]\!] \rightarrow [0,1]$ and the $t_{30\%}$ defined as:

$$t_{30\%} = min\left(\{n \in [\![0, N]\!], \forall i \in [\![n, N]\!], w(i) \leq 0.3 \times max(w)\}\right)$$

A wave with a smaller $t_{30\%}$ value means the pandemic have been efficiently controlled. History waves of different countries/regions with different implemented NPIs were classified and listed in Supplementary Table S1. $t_{30\%}$ of each history wave were calculated, and the average $t_{30\%}$ of each corresponding NPIs are presented in the table. Average value of $t_{30\%}$ were only for the history wave after July 2020, considering that in most parts of the world, the new case number of the COVID-19 after July 2020 was much higher than before.

REFERENCES

1. World Health Organization. Coronavirus disease (COVID-19) weekly epidemiological update and weekly operational update. 2021. https:www.who.int/emergencies/diseases/novel-coronavirus-2019/situation-reports/. [2021-4-10].
2. Mathieu E, Ritchie H, Roser M. Our World in Data is now tracking Coronavirus (COVID-19) vaccinations across the world. 2021. https://ourworldindata.org/covid-vaccination-dataset. [2021-4-10].