Discrete simulation analysis of COVID-19 and prediction of isolation bed numbers

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Abstract

Background. The outbreak of COVID-19 has been defined by the World Health Organization as a pandemic, and containment depends on traditional public health measures. However, the explosive growth of the number of infected cases in a short period of time has caused tremendous pressure on medical systems. Adequate isolation facilities are essential to control outbreaks, so this study aims to quickly estimate the demand and number of isolation beds.

Methods. We established a discrete simulation model for epidemiology. By adjusting or fitting necessary epidemic parameters, the effects of the following indicators on the development of the epidemic and the occupation of medical resources were explained: (1) incubation period, (2) response speed and detection capacity of the hospital, (3) disease healing time, and (4) population mobility. Finally, a method for predicting the number of isolation beds was summarized through multiple linear regression. This is a city level model that simulates the epidemic situation from the perspective of population mobility.

Results. Through simulation, we show that the incubation period, response speed and detection capacity of the hospital, disease healing time, degree of population mobility, and infectivity of cured patients have different effects on the infectivity, scale, and duration of the epidemic.

43 Among them, (1) incubation period, (2) response speed and detection capacity of the hospital, (3)
44 disease healing time, and (4) population mobility have a significant impact on the demand and
45 number of isolation beds ($P < 0.05$), which agrees with the following regression equation: $N = P$
46 $* (-0.273 + 0.009I + 0.234M + 0.012T_1 + 0.015T_2) * (1+V)$.
47

Introduction

49 SARS-CoV-2 is a novel coronavirus that has the ability of human-to-human transmission(Lu et
50 al. 2020; Xie & Chen 2020). Coronavirus disease 2019 (COVID-19) caused by SARS-CoV-2
51 has been defined by the World Health Organization (WHO) as a pandemic (the worldwide
52 spread of a new disease) (WHO). As of April 5, 2020, more than 1100000 cases of COVID-19
53 have been reported in different countries and territories (WHO 2020). Researchers around the
54 world are making every effort to clarify the prevention and control strategy of SARS-CoV-2
55 (Chen et al. 2020; Hoffmann et al. 2020; Liang et al. 2020).
56 COVID-19 is extremely contagious, and its explosive growth in a short space of time has caused
57 tremendous pressure on medical resources (Bai et al. 2018). Conventional medical conditions
58 have difficulty meeting the needs of the detection capability for suspected cases and the number
59 of isolation beds for treatment and isolation (Khan et al. 2020; Remuzzi & Remuzzi ; Spina et al.
60 2020). The number of isolation beds is crucial to reduce the scale of infection and reduce the
61 number of fatalities. Too few isolation beds can lead to the continuation of the epidemic, and too
62 many isolation beds may cause waste and environmental damage (Bedford et al. 2020; Martinez-
63 Alvarez et al. ; Shah et al.).
64 To explore a number of isolation beds, we established a discrete simulation model of epidemics
65 based on COVID-19. By setting several different epidemic indicators we analyzed the changing
66 laws of the epidemic situation, peak value, and scale of the epidemic in different situations. In
67 particular, we pay attention to the occupation of medical resources during the outbreak. We
68 summarized some epidemic indicators related to the number of isolation beds through multiple
69 linear regression and estimated the number of isolation beds through these indicators.
70 The conclusion is practical, which can provide support for the scheduling of medical resources
71 and the search for effective solutions in the current outbreak or in similar future outbreaks.
72

Materials & Methods

74 **1 Establishment of discrete simulation model and parameter interpretation**
75 **1.1 Parameter interpretation**
76 Normal: The health status of the citizens in the city simulation model.
77 Shadow: Too close to patients who have not been isolated, may be infected, and contagious.
78 Supershadow: Different from the general incubation period, it has a longer incubation period and
79 is infectious.
80 Suspected: Refers to the suspected state after the incubation period and is infectious.
81 Confirmed: Refers to the state of being diagnosed with the disease after the hospital's response
82 time. The state has changed from a state of suspected disease and is infectious.

83   Isolated: Refers to the isolated state of being injected into the hospital after the diagnosis, and the
84   bed needs to be occupied.
85   Cured: Refers to the cured state after being diagnosed and can be transferred out of the hospital
86   to vacate the bed.
87   Dead: Refers to the death state of a person who died of illness during the epidemic and no longer
88   has the intention of mobility.
89   Population mobility rate: The percentage of the population that has willingness to move.
90   Healing time: The mean time between being in isolation and being discharged.
91   Incubation period: The time from infection to self-detection of suspected symptoms.
92   Fatality rate: The probability of death after diagnosis.
93   Dead time: Mean time from diagnosis to death.
94   Hospital response time: The time from the patient's suspected symptoms to a definitive
95   diagnosis.
96   Transmission rate: The probability of being infected by contact with an infected person within an
97   unsafe distance.
98   **1.2 Establishment of the discrete simulation model**
99   In this discrete simulation model, we use the Java language to carry out object-oriented
100   programming. The eight states of people were defined as normal, shadow, supershadow,
101   suspected, confirmed, isolated, cured, and dead. At the same time, for the times of being
102   infected, suspected, confirmed, isolated, cured, and died were independent attributes configured
103   to simulate the process with the actual world process, so the program can produce all attributes,
104   including each moment, and record, analyze and calculate the statistics for each simulation
105   individual.
106   In the model, the length of the incubation period, the time from being a suspected case to being
107   diagnosed, the length of isolation, the rate of population mobility, the probability of infection,
108   and the probability of death after infection can be adjusted or fitted as the necessary parameters
109   for simulation. Most of the time, the parameters follow the normal distribution model, and the
110   mean and standard deviation are defined by the parameters. The probability follows the random
111   number model. In each specific model, the simulation value of the random number model will be
112   given in details. The simulation object state transition logic is shown in Figure 1.
113   **1.3 General assumptions**
114   a. During the simulation process, the total population of the city is constant, and the number of
115   initial cases is known.
116   b. The incubation period (shadow time), time of death (died time) and time of cure (cured time)
117   of an individual were in accordance with the normal distribution.
118   c. There is a fixed response time interval between the onset of patient symptoms and the moment
119   of hospital diagnosis. The hospital always has enough resources to make a diagnosis when the
120   response time is reached.
121   d. When exposed to an infected person within a dangerous distance, the probability of infection
122   and death after infection is constant.

123   e. After being cured, the hospital will discharge the patient and be released from isolation at

124   once.

125   f. Unless otherwise specified, these characteristics do not change over time during disease

126   transmission.

127   g. The simulation model ends when all patients have been discharged.

128   h. The patient can not be contagious or infected again after being cured.

129   **2 Model parameters setting**

130   In order to prevent deviations in the simulation process, each set of parameters was repeated 10

131   times. After removing outliers, the mean was used to draw the curve and analysis.

132   **2.1 Impact of the incubation period on the epidemic development**

133   This model is used to discuss the influence of the disease incubation period on epidemic

134   infection and medical resource occupation. In this model, we make the assumption that the

135   hospital's isolation capacity is strong enough to admit all patients.

136   To achieve a single variable, we assign the following parameters: the total population=5000,

137   number of initially infected persons=20, population mobility rate=1, healing time=15 days

138   (standard deviation=2 days), hospital response time=1 day, fatality rate=0.05, and dead time=10

139   days (standard deviation=5 days) remained the same during the simulation. The experimental

140   groups were as follows: the mean incubation period was set at 3, 7, 10, 14 and 21 days.

141   **2.2 Impact of the hospital response time on the epidemic development**

142   This model is used to discuss the impact of the hospital response time on epidemic infection and

143   medical resource occupation. In this model, the hospital's isolation capacity is strong enough to

144   admit all patients.

145   To achieve a single variable, we assign the following parameters: the total population=5000,

146   number of initially infected persons=20, incubation period=7 days (standard deviation=5 days),

147   population mobility rate=1, healing time=15 days (standard deviation=2 days), fatality rate=0.05,

148   and dead time=10 days (standard deviation=5 days) remained the same during the simulation.

149   The experimental groups were as follows: the hospital response time was set at 1, 3, 5, 7 and 10

150   days.

151   **2.3 Impact of the healing time on the epidemic development**

152   This model is used to discuss the influence of the hospital healing time on the epidemic infection

153   and medical resource occupation. In this model, the hospital's isolation capacity is strong enough

154   to admit all patients.

155   To achieve a single variable, we assign the following parameters: the total population=5000,

156   number of initially infected persons=20, incubation period=7 days (standard deviation=5 days),

157   population mobility rate=1, hospital response time=1 day, fatality rate=0.05, and dead time=10

158   days (standard deviation=5 days) remained the same during the simulation. The experimental

159   groups were as follows: the hospital healing time was set at 5, 7, 10, 15 and 20 days

160   **2.4 Impact of the population mobility on the epidemic development**

161 This model was used to discuss the influence of the population mobility on the epidemic infection
162 and medical resource occupation. In this model, the hospital's isolation capacity is strong enough
163 to admit all patients.
164 To achieve a single variable, we assign the following parameters: the total population=5000,
165 number of initially infected persons=20, incubation period=7 days (standard deviation=5 days),
166 hospital response time=1 day, healing time=15 days (standard deviation=2 days), fatality
167 rate=0.05, and dead time=10 days (standard deviation=5 days) remained the same during the
168 simulation. The experimental groups were as follows: the population flow rate was set to 0, 30%,
169 50%, 80% and 100%.
170 **2.5 Impact of the hospital isolation capacity on the infection situation**
171 This model was used to discuss the influence of the hospital isolation capacity on the epidemic
172 infection.
173 To achieve a single variable, we assign the following parameters: the total population=5000,
174 number of initially infected persons=20, incubation period=7 days (standard deviation=5 days),
175 population mobility rate=1, hospital response time=1 day, healing time=15 days (standard
176 deviation=2 days), fatality rate=0.05, and dead time=10 days (standard deviation=5 days)
177 remained the same during the simulation. The experimental groups were as follows: the hospital
178 isolation capacity was set to 40%, 60%, 80% and 100%.
179 **3 Multiple regression analysis and parameter prediction of the number of isolation facilities**
180 Multilinear regression (MLR) analysis was used to evaluate the impact of the simulation
181 parameters on the dependent variable demand for the number of isolation beds. Meanwhile, the
182 prediction method was applied to an example under different healing times to test the accuracy.
183 **4 Statistical analysis**
184 Continuous variables are compared using the average. Using SPSS v26.0 (IBM authorized
185 Central South University to use) for data analysis, analysis of variance (ANOVA) was used to
186 analyze the level of significant difference between the groups. When the variance is
187 homogeneous, the least significant difference (LSD) method and multiple comparisons are used
188 to analyze between any two groups; when the variance is not homogeneous, Tamhane's T2 tests
189 and the multiple comparison are used to compare the mean between any two groups. The
190 Grubbs method was used to address outliers. For all statistical analyses, the test level was α =
191 0.05.
192 R is used to represent the goodness of fit of the multiple regression to measure the fitting degree
193 of the estimated model to the observed values. The table of regression analysis lists the results of
194 the significance test of independent variables (using t-test) and the P value of t-test, indicating
195 whether independent variables have a significant influence on dependent variables.
196
197 **Results**
198 **1 Impact of epidemic factors on the infection situation under sufficient isolation facilities**
199 **1.1 Impact of incubation period on the epidemic development**

200 The incubation period is an asymptomatic stage in the early stages of disease development, at
201 which point patients themselves will not suspect that they have been infected. We compared the
202 infection situation of different incubation periods. ANOVA showed that the mean values of all
203 indicators among groups were not exactly the same (P<0.05). The detailed differences among
204 groups are shown in Table 1.
205 Further analysis was performed using multiple comparisons. The maximum number of
206 incubation cases, the sum of infected cases and the corresponding date for the peak number of
207 inpatients were significantly different between any two groups (P<0.05). The long incubation
208 period promoted these epidemic indicators. We use the Basic Reproduction Number(R0) to
209 describe the rate of infection of an epidemic. This value can reflect the possibility and severity of
210 an infectious disease outbreak. Basic Reproduction Number (R0) refers to the number of people
211 who can be infected by an average patient in an environment with all susceptible people without
212 intervention. For common epidemics, R0 will be bigger than one. In addition, Effective
213 Reproduction Number(Rt) represents the average number of patients that can be infected at a
214 certain moment in the process of disease transmission and development, with the addition of
215 prevention and control interventions, such as isolation of patients in shelters, isolation of
216 individuals at home, and wearing masks. The maximum number of newly confirmed cases and
217 their corresponding dates, corresponding date of peak incubation cases, maximum value of Rt,
218 duration of the epidemic, and maximum number of inpatients were not exactly equal among the
219 groups in different incubation periods, and there were significant differences among some groups
220 (P<0.05). The above indicators increased with the increase in the incubation period. (Figure 2)
221 **1.2 Impact of the hospital response time on the epidemic development**
222 In the simulation model, hospital response time refers to the time it takes for a patient to develop
223 a first symptom until a clear diagnosis is obtained. This time is extended if the patient is
224 unwilling to go to the hospital to undergo detection testing, if the hospital detection method fails
225 to diagnose the disease early, or if there are insufficient hospital detection reagents.
226 ANOVA showed that there were no significant differences in the corresponding date of the
227 maximum number of incubation cases among different response time groups (P>0.05), and the
228 mean of the other indicators among the groups was not exactly equal (P<0.05). The detailed
229 differences among the groups are shown in Table 2.
230 The multiple comparisons showed that the sum of infected cases between any two groups was
231 significantly different (P<0.05). The sum of the infected cases increased with the extension of
232 response time. The maximum number of newly confirmed cases and its corresponding date, the
233 maximum number of incubation cases, the maximum of Rt, the duration of the epidemic, the
234 maximum number of inpatients and its corresponding date were not exactly equal among the
235 groups at different response times, and there were significant differences among some groups
236 (P<0.05). The above indicators increased with the extension of the response time (Figure 3).
237 **1.3 Impact of the healing time on the epidemic development**
238 The healing time refers to the average time from admission to discharge. ANOVA showed that
239 the mean values of the maximum value of Rt, the maximum number of inpatients and their

240   corresponding dates among different healing time groups were not exactly the same (P<0.05),

241   and the other indicators were not considered to be significantly different (P>0.05). The detailed

242   differences among the groups are shown in Table 3.

243   Further multiple comparisons showed that the maximum number of inpatients between any two

244   groups was significantly different (P<0.05). The maximum number of inpatients increased with

245   the extension of the healing time. The maximum value of Rt and the corresponding date of peak

246   inpatient number were not exactly equal among the groups at different healing times, and there

247   were significant differences among some groups (P<0.05). The extension of the healing period

248   promoted the increase in the above indicators (Figure 4).

249   **1.4 Impact of the population mobility on the epidemic development**

250   The population mobility rate refers to the proportion of people in motion to the total population.

251   We compared the infection situation of different population mobility rates. ANOVA showed that

252   there were no significant differences in the maximum value of Rt and the duration of the

253   epidemic among the groups (P>0.05), and the mean of other indicators among the groups was

254   not exactly equal (P<0.05). The detailed differences among the groups are shown in Table 4.

255   The multiple comparisons showed that the sum of the infected cases between any two groups

256   was significantly different (P<0.05). The increase in the population mobility rate caused a higher

257   sum of the infected cases. The maximum number of newly confirmed cases and its

258   corresponding date, the maximum number of incubation cases and its corresponding date, the

259   maximum number of inpatients and their corresponding dates were not exactly equal among the

260   groups in different population mobility rates, and there were significant differences among some

261   groups (P<0.05). Among them, the maximum number of newly confirmed cases, the maximum

262   number of incubation cases and the maximum number of inpatients increased with the increase

263   in the population activity rate. At the extreme value of 0%, that is, when everyone was inactive,

264   the corresponding date of peak incubation cases and the corresponding date of

265   peak inpatient number were significantly advanced, which was significantly different from that

266   of the other groups (Figure 5).

267   **2 Impact of the hospital isolation capacity on the infection situation**

268   The hospital isolation capacity is defined by the proportion of the actual quantity of isolation

269   beds to the demanded quantity for isolation beds. ANOVA showed that there were no significant

270   differences in the maximum number of newly confirmed cases, the maximum number of

271   incubation cases and the maximum value of Rt among different isolation capacity groups

272   (P>0.05), and the mean of the other indicators among the groups was not exactly equal (P<0.05).

273   The detailed differences among groups are shown in Table 5.

274   The multiple comparisons showed that the corresponding dates of the peak number of inpatients

275   and the duration of isolation facilities at their full capacity between any two groups were

276   significantly different (P<0.05). The corresponding date of the peak inpatient number was

277   delayed with the decrease in isolation capacity. The duration of isolation facilities at their full

278   capacity increased with the lack of isolation beds, which showed a quadratic relationship

279   (Supplementary Table 1, Supplementary Figure 1). In addition, the corresponding date of peak

280 newly confirmed cases, the corresponding date of incubation cases, the sum of infected cases and
281 the duration of the epidemic were not exactly equal among the groups, and there were significant
282 differences among some groups (P<0.05). In the severely inadequate isolation capacity group
283 (40%), the corresponding date of incubation cases, the mean value of Rt, the sum of infected
284 cases and the duration of the epidemic were significantly increased (P<0.05) (Figure 6).
285 **3 Multiple regression analysis and parameter prediction of the number of isolation facilities**
286 **3.1 Multivariate regression analysis**
287 To further explore the rational setting of isolation beds in the medical system under multifactor
288 epidemic conditions, we analyzed the relationship between different epidemic indicators and a
289 number of isolation beds by multiple regression analysis. The t-test showed that the independent
290 variables of incubation period, population mobility rate, hospital response time and healing time
291 significantly affected the number of isolation beds (P<0.05) (Table 6). Finally, we obtained the
292 following regression equation (R^2=0.841):
293 $N = P * (-0.273 + 0.009I + 0.234M + 0.012T1 + 0.015T2) * (1+V)$
294 N indicates a number of isolation beds. P represents population, which refers to the total
295 population in the corresponding area. I represents incubation period of the epidemic. M
296 represents population mobility rate, which refers to the proportion of people in motion to the
297 total population. T1 represents hospital response time, which refers to the time it takes for a
298 patient to develop the first symptom until a clear diagnosis is obtained. T2 represents healing
299 time, which refers to the average time from admission to discharge. T1 and T2 can be estimated
300 based on a certain number of cases. Considering that a certain number of isolation beds should
301 be reserved to cope with emergency situations, we set V as the reserve amount. This article
302 suggests that it is generally reserved at 10% according to the simulation results.
303 **3.2 Prediction of a number of isolation beds in different healing times**
304 Here, the prediction method was applied to an example (Figure 7). The predicted number of
305 isolation beds were basically consistent with the model operating results. The parameter setting
306 is the same as model 2.3.
307

Discussion

309 **1 Impact of the incubation period on the epidemic development**
310 According to result 1.1, we found that a longer incubation period significantly promoted the
311 infectivity, scale and duration of the epidemic. By tracking this phenomenon, it was found that
312 the patients in the incubation period and without mobility restriction caused a high level of
313 transmission before displaying symptoms by contacting others, which was similar to the views of
314 Li P and Jiang X et al. (Jiang et al. 2020; Li et al. 2020). To contain an outbreak, early detection
315 of suspected cases is critical (De Salazar et al. 2020). Some studies have described that a longer
316 incubation period may be beneficial for epidemic control (Kahn et al. 2020), as this allows the
317 Centers for Disease Control and Prevention (CDC) to have more time to deal with the overall
318 epidemic. This conclusion may be more applicable to some known diseases, but for unknown
319 diseases, we believe that a longer incubation period represents a more dangerous signal, making

320   the development of the epidemic uncontrollable(Kahn et al. 2020; Lauer et al. 2020). Due to the
321   reduced predictability of the disease outbreak scale, it is more difficult to track patients. As a
322   result, the disease may spread to a wider range of people, making it difficult to control.
323   Our results showed that increasing hospital response speed could improve infectivity and scale of
324   an outbreak, which is consistent with previous research(Chan et al. 2020; Hellewell et al. 2020;
325   Wu et al. 2020). Shortening the hospital response time depends on the public's awareness of
326   epidemic prevention and the level of medical technology. On the one hand, the public needs to
327   pay more attention to the epidemic and actively cooperate with early detection; on the other
328   hand, medical technology determines the time it takes for the detection method to give an
329   accurate result. In addition, if sufficient isolation facilities can be provided, the centralized
330   isolation of all suspected patients who cannot be excluded can also help reduce the hospital
331   response time (Bai et al. 2018; Chen et al.).
332   Compared with the hospital response time, the impact of the population mobility rate on the
333   duration of the epidemic is not significant in the case of abundant medical resources. However,
334   unrestricted population mobility can cause a large medical load and consumption of medical
335   supplies and will generate a large number of infected cases, resulting in adverse socioeconomic
336   impacts (Kraemer et al. 2020; Tian et al. 2020; Yang et al. 2020). In the actual epidemic
337   situation, the amount of medical resources will be less and more scarce than usual. Therefore, it
338   cannot be considered that the population mobility has no effect on the duration of the outbreak.
339   The detailed consequences of inadequate medical resources are discussed in section 3.2. In
340   extreme cases, all people stopped activities, i.e., when the mobility rate is 0%, the overall scale
341   of the epidemic is dramatically reduced, and the corresponding date of the epidemic peak sharply
342   advances. It is speculated that the disease may saturate in a small area after taking this extreme
343   prevention and control measure; thus, the transmission will be completely blocked. Since there is
344   no new-generation infection, different transmission laws are displayed.
345   **2 Impact of insufficient isolation facilities on the epidemic development**
346   There is no specific treatment or vaccine for COVID-19 at the time of the conceptualization of
347   the simulation model, containment of the epidemic depends more on traditional public health
348   measures (Wilder-Smith & Freedman 2020). The results showed that the low capacity of hospital
349   isolation would lead to serious consequences. This is consistent with previous studies showing
350   that intervention through timely isolation measures is effective in controlling the epidemic
351   (Fraser et al. 2004; Rocklov et al. 2020). Even with vaccines, adequate isolation beds are a key
352   factor in controlling the outbreak. In our model, if you need to simulate the possession of a
353   vaccine, you can simply modify the total population. The method is to update this constant to
354   subtract the number of people immunized.
355   In addition, the simulation model showed that the duration of isolation facilities at full capacity
356   showed a quadratic relationship with the gap in the number of isolation facilities. That is, as the
357   gap in the number of isolated beds expands, the growth rate of full-load time gradually
358   accelerates, which may increase the uncontrollability of the epidemic. In our model, the hospital
359   isolation capacity does not affect the ability of to detect the disease and diagnosis patients, so it

360   has no significant effect on the maximum number of newly confirmed cases and their
361   corresponding dates. However, the increase in the duration of isolation facilities at full load
362   shows a more severe overload of the medical system. Thus, under the condition of insufficient
363   isolation capacity, expanding the original size of the hospital or constructing Fangcang shelter
364   hospitals are the key measures to contain outbreaks (Chen et al. ; Khan et al. 2020; Wu &
365   McGoogan 2020).

366   **3 Multiple regression analysis and parameter prediction of the number of isolation facilities**
367   We summarized the related factors that affected the demanded quantity of isolation beds by
368   multiple regression analysis. Furthermore, multivariate regression analysis was used to estimate
369   the number of isolation beds:
370   $N = P * (-0.273 + 0.009I + 0.234M + 0.012T1 + 0.015T2) * (1+V)$
371   The regression equation shows that the population mobility rate is the variable with the highest
372   weight, which indicates that the restriction of population mobility is the critical factor to contain
373   outbreaks and effectively reduce the load on the medical system (Liao et al. 2020; Ng et al. 2020;
374   Tian et al. 2020; Wu et al. 2020). We believe that reducing the epidemic scale by restricting
375   population mobility can also help to provide time for the establishment of temporary isolation.
376   In practice, the incubation period (I) can be estimated from the time between traceable harmful
377   exposure to the time of the first symptom (Backer et al. 2020; Lauer et al. 2020). The population
378   mobility rate (M) can be roughly estimated by the ratio of the population in unrestricted mobility,
379   including medical personnel and administrative personnel, to the total population. (Telionis et al.
380   2020; Wu et al. 2020). Hospital response time (T1) and healing time (T2) can be estimated based
381   on a certain number of cases. In addition, we recommend V = 10% as a reserve to address
382   emergency situations under actual conditions. The above indicators are easy to obtain and
383   estimate, which provides a feasible guarantee for using this method to estimate a number of
384   isolation facilities.
385   More importantly, estimating the number of isolation facilities based on the epidemic situation
386   and relevant parameters of the medical system will help to predict the pressure of the medical
387   system in different areas in advance. This will provide decision-making support for the rational
388   arrangement of medical resources and epidemic control.

389   **4 Advantages and limitations of this study**
390   Based on the data we sampled, the simulation model proposed in the manuscript can analyze the
391   common parameters of infectious diseases and the related laws of transmission in the case of a
392   single variable. However, we must admit that this model is still preliminary. As researchers of
393   this issue, we have summarized the advantages and limitations of the study.
394   Advantage:(1) The established simulation program is controlled by computer advanced language
395   software, using multi-threaded parallel operation methods. It can produce results quickly. (2) The
396   simulation program is convenient, and the modification parameters can be subsequently analyzed
397   for different types of epidemic. The output value is a continuous variable, which is good for
398   statistical analysis. (3) Parametric assumptions based on data analysis are established in a virtual
399   environment, which is conducive to early warning of risks.

400 Limitation: (1) This study attempts to put forward a more general model to simulate the process
401 of disease transmission. But in fact, we only tested on part of the COVID-19 data. If the model is
402 removed from this environment, it may produce large errors. (2) In this model, we consider many
403 common parameters, most of which we give suggestions for interpretation and value in the
404 paper. If we want to pursue higher accuracy of the model, we strongly suggest that the model
405 should be verified by the local actual situation in the early stage.
406

407 ## Conclusions
408 The incubation period, response speed detection capacity of the hospital, disease healing time,
409 and degree of population mobility have different effects on the infectivity, scale, duration of the
410 epidemic, and the demand and number of isolation beds. Adequate isolation facilities are
411 essential to control outbreaks. The prediction equation can be easily and quickly applied to
412 estimate the demand number of isolation beds in a COVID-19-affected city. This study will
413 provide decision-making support for the rational arrangement of medical resources and epidemic
414 control.
415

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429

430 ## Data availability

431 The codes of the current study are available in the GitHub repository,
432 https://github.com/coolleafly/COV_SIM/. The average data generated by 10 simulations for each
433 model are included in this published article (and its supplementary information files). If readers
434 have research needs on other data, please contact the corresponding author
435

436 ## References

437 Backer JA, Klinkenberg D, and Wallinga J. 2020. Incubation period of 2019 novel coronavirus
438   (2019-nCoV) infections among travellers from Wuhan, China, 20-28 January 2020. Euro
439   Surveill 25. 10.2807/1560-7917.es.2020.25.5.2000062

440   Bai S, Yu BG, Zhang YZ, Ding H, Wu ZW, Fan B, Fan HJ, Hou SK, and Chen F. 2018.
441   Challenges of Treating Adenovirus Infection: Application of a Deployable Rapid-
442   Assembly Shelter Hospital. Disaster Med Public Health Prep 12:109-114.
443   10.1017/dmp.2016.187
444   Bedford J, Enria D, Giesecke J, Heymann DL, Ihekweazu C, Kobinger G, Lane HC, Memish Z,
445   Oh M-d, Sall AA, Schuchat A, Ungchusak K, and Wieler LH. 2020. COVID-19: towards
446   controlling of a pandemic. The Lancet 395:1015-1018. 10.1016/S0140-6736(20)30673-5
447   Chan JF, Yip CC, To KK, Tang TH, Wong SC, Leung KH, Fung AY, Ng AC, Zou Z, Tsoi HW,
448   Choi GK, Tam AR, Cheng VC, Chan KH, Tsang OT, and Yuen KY. 2020. Improved
449   molecular diagnosis of COVID-19 by the novel, highly sensitive and specific COVID-19-
450   RdRp/Hel real-time reverse transcription-polymerase chain reaction assay validated in
451   vitro and with clinical specimens. J Clin Microbiol. 10.1128/jcm.00310-20
452   Chen N, Zhou M, Dong X, Qu J, Gong F, Han Y, Qiu Y, Wang J, Liu Y, Wei Y, Xia J, Yu T,
453   Zhang X, and Zhang L. 2020. Epidemiological and clinical characteristics of 99 cases of
454   2019 novel coronavirus pneumonia in Wuhan, China: a descriptive study. Lancet
455   395:507-513. 10.1016/s0140-6736(20)30211-7
456   Chen S, Zhang Z, Yang J, Wang J, Zhai X, Bärnighausen T, and Wang C. Fangcang shelter
457   hospitals: a novel concept for responding to public health emergencies. The Lancet.
458   10.1016/S0140-6736(20)30744-3
459   De Salazar PM, Niehus R, Taylor A, Buckee CO, and Lipsitch M. 2020. Identifying Locations
460   with Possible Undetected Imported Severe Acute Respiratory Syndrome Coronavirus 2
461   Cases by Using Importation Predictions. Emerg Infect Dis 26. 10.3201/eid2607.200250
462   Fraser C, Riley S, Anderson RM, and Ferguson NM. 2004. Factors that make an infectious
463   disease outbreak controllable. Proc Natl Acad Sci U S A 101:6146-6151.
464   10.1073/pnas.0307506101
465   Hellewell J, Abbott S, Gimma A, Bosse NI, Jarvis CI, Russell TW, Munday JD, Kucharski AJ,
466   Edmunds WJ, Funk S, and Eggo RM. 2020. Feasibility of controlling COVID-19
467   outbreaks by isolation of cases and contacts. Lancet Glob Health 8:e488-e496.
468   10.1016/s2214-109x(20)30074-7
469   Hoffmann M, Kleine-Weber H, Schroeder S, Kruger N, Herrler T, Erichsen S, Schiergens TS,
470   Herrler G, Wu NH, Nitsche A, Muller MA, Drosten C, and Pohlmann S. 2020. SARS-
471   CoV-2 Cell Entry Depends on ACE2 and TMPRSS2 and Is Blocked by a Clinically
472   Proven Protease Inhibitor. Cell. 10.1016/j.cell.2020.02.052
473   Jiang X, Rayner S, and Luo MH. 2020. Does SARS-CoV-2 has a longer incubation period than
474   SARS and MERS? J Med Virol 92:476-478. 10.1002/jmv.25708
475   Kahn R, Peak CM, Fernandez-Gracia J, Hill A, Jambai A, Ganda L, Castro MC, and Buckee CO.
476   2020. Incubation periods impact the spatial predictability of cholera and Ebola outbreaks
477   in Sierra Leone. Proc Natl Acad Sci U S A 117:5067-5073. 10.1073/pnas.1913052117
478   Khan S, Siddique R, Ali A, Xue M, and Nabi G. 2020. Novel coronavirus, poor quarantine, and
479   the risk of pandemic. J Hosp Infect. 10.1016/j.jhin.2020.02.002
480   Kraemer MUG, Yang C-H, Gutierrez B, Wu C-H, Klein B, Pigott DM, du Plessis L, Faria NR,
481   Li R, Hanage WP, Brownstein JS, Layan M, Vespignani A, Tian H, Dye C, Pybus OG,
482   and Scarpino SV. 2020. The effect of human mobility and control measures on the
483   COVID-19 epidemic in China. Science:eabb4218. 10.1126/science.abb4218
484   Lauer SA, Grantz KH, Bi Q, Jones FK, Zheng Q, Meredith HR, Azman AS, Reich NG, and
485   Lessler J. 2020. The Incubation Period of Coronavirus Disease 2019 (COVID-19) From

486   Publicly Reported Confirmed Cases: Estimation and Application. Ann Intern Med.
487   10.7326/m20-0504
488   Li P, Fu JB, Li KF, Chen Y, Wang HL, Liu LJ, Liu JN, Zhang YL, Liu SL, Tang A, Tong ZD,
489   and Yan JB. 2020. Transmission of COVID-19 in the terminal stage of incubation period:
490   a familial cluster. Int J Infect Dis. 10.1016/j.ijid.2020.03.027
491   Liang Y, Xu D, Fu S, Gao K, Huan J, Xu L, and Li J-d. 2020. A Simple Prediction Model for the
492   Development Trend of 2019-nCov Epidemics Based on Medical Observations. arXiv e-
493   prints. p arXiv:2002.00426.
494   Liao WB, Ju K, Gao YM, and Pan J. 2020. The association between internal migration and
495   pulmonary tuberculosis in China, 2005-2015: a spatial analysis. Infect Dis Poverty 9:5.
496   10.1186/s40249-020-0621-x
497   Lu R, Zhao X, Li J, Niu P, Yang B, Wu H, Wang W, Song H, Huang B, Zhu N, Bi Y, Ma X,
498   Zhan F, Wang L, Hu T, Zhou H, Hu Z, Zhou W, Zhao L, Chen J, Meng Y, Wang J, Lin
499   Y, Yuan J, Xie Z, Ma J, Liu WJ, Wang D, Xu W, Holmes EC, Gao GF, Wu G, Chen W,
500   Shi W, and Tan W. 2020. Genomic characterisation and epidemiology of 2019 novel
501   coronavirus: implications for virus origins and receptor binding. Lancet 395:565-574.
502   10.1016/s0140-6736(20)30251-8
503   Martinez-Alvarez M, Jarde A, Usuf E, Brotherton H, Bittaye M, Samateh AL, Antonio M,
504   Vives-Tomas J, D'Alessandro U, and Roca A. COVID-19 pandemic in west Africa. The
505   Lancet Global Health. 10.1016/S2214-109X(20)30123-6
506   Ng Y, Li Z, Chua YX, Chaw WL, Zhao Z, Er B, Pung R, Chiew CJ, Lye DC, Heng D, and Lee
507   VJ. 2020. Evaluation of the Effectiveness of Surveillance and Containment Measures for
508   the First 100 Patients with COVID-19 in Singapore - January 2-February 29, 2020.
509   MMWR Morb Mortal Wkly Rep 69:307-311. 10.15585/mmwr.mm6911e1
510   Remuzzi A, and Remuzzi G. COVID-19 and Italy: what next? The Lancet. 10.1016/S0140-
511   6736(20)30627-9
512   Rocklov J, Sjodin H, and Wilder-Smith A. 2020. COVID-19 outbreak on the Diamond Princess
513   cruise ship: estimating the epidemic potential and effectiveness of public health
514   countermeasures. J Travel Med. 10.1093/jtm/taaa030
515   Shah J, Karimzadeh S, Al-Ahdal TMA, Mousavi SH, Zahid SU, and Huy NT. COVID-19: the
516   current situation in Afghanistan. The Lancet Global Health. 10.1016/S2214-
517   109X(20)30124-8
518   Spina S, Marrazzo F, Migliari M, Stucchi R, Sforza A, and Fumagalli R. 2020. The response of
519   Milan's Emergency Medical System to the COVID-19 outbreak in Italy. The Lancet
520   395:e49-e50. 10.1016/S0140-6736(20)30493-1
521   Telionis PA, Corbett P, Venkatramanan S, and Lewis B. 2020. Methods for Rapid Mobility
522   Estimation to Support Outbreak Response. Health Secur 18:1-15. 10.1089/hs.2019.0101
523   Tian H, Liu Y, Li Y, Wu C-H, Chen B, Kraemer MUG, Li B, Cai J, Xu B, Yang Q, Wang B,
524   Yang P, Cui Y, Song Y, Zheng P, Wang Q, Bjornstad ON, Yang R, Grenfell BT, Pybus
525   OG, and Dye C. 2020. An investigation of transmission control measures during the first
526   50 days of the COVID-19 epidemic in China. Science:eabb6105.
527   10.1126/science.abb6105
528   WHO. Rolling updates on coronavirus disease (COVID-19). Available at
529   https://www.who.int/emergencies/diseases/novel-coronavirus-2019/events-as-they-
530   happen.

531 WHO. 2020. Coronavirus disease (COVID-2019) situation reports. Available at
532   https://www.who.int/emergencies/diseases/novel-coronavirus-2019/situation-reports.
533 Wilder-Smith A, and Freedman DO. 2020. Isolation, quarantine, social distancing and
534   community containment: pivotal role for old-style public health measures in the novel
535   coronavirus (2019-nCoV) outbreak. J Travel Med. 10.1093/jtm/taaa020
536 Wu JT, Leung K, and Leung GM. 2020. Nowcasting and forecasting the potential domestic and
537   international spread of the 2019-nCoV outbreak originating in Wuhan, China: a
538   modelling study. Lancet 395:689-697. 10.1016/s0140-6736(20)30260-9
539 Wu Z, and McGoogan JM. 2020. Characteristics of and Important Lessons From the Coronavirus
540   Disease 2019 (COVID-19) Outbreak in China: Summary of a Report of 72314 Cases
541   From the Chinese Center for Disease Control and Prevention. Jama.
542   10.1001/jama.2020.2648
543 Xie M, and Chen Q. 2020. Insight into 2019 novel coronavirus - an updated intrim review and
544   lessons from SARS-CoV and MERS-CoV. Int J Infect Dis. 10.1016/j.ijid.2020.03.071
545 Yang W, Deng M, Li C, and Huang J. 2020. Spatio-Temporal Patterns of the 2019-nCoV
546   Epidemic at the County Level in Hubei Province, China. Int J Environ Res Public Health
547   17. 10.3390/ijerph17072563
548

Figure 1

Logical flowchart of the simulation object status transition.

The eight states of people were defined as normal, shadow, supershadow, suspected, confirmed, isolated, cured, and dead. The times of being infected, suspected, confirmed, isolated, cured, and died were independent attributes configured. The length of the incubation period, the time from being a suspected case to being diagnosed, the length of isolation, the rate of population mobility, the probability of infection, and the probability of death after infection can be adjusted or fitted as the necessary parameters for simulation.

The normal

No

random<broad rate?

Yes

unsafe distance?

Yes

No

No

random<super shadow rate?

Yes

The shadow

The super shadow

get the shadow time

No

get the super shadow time

shadow time is ended up to now?

No

Yes

get the suspected moment

from suspected moment to now has reached the hospital response time?

The suspected

Yes

get the die moment

No

random<diagnosis rate?

Yes

The confirmed

No

the hospital has empty bed?

get the cured moment

Yes

The quarantined

die moment has reached up to now?

No

No

cured moment is prior to die moment?

Yes

Yes

No

The death

cured moment has reached up to now?

Yes

Yes

random<out hospital shadow?

Yes

No

The cured

No

unsafe diastance?

Yes

No

random<cured broad rate?

Yes

Figure 2

Epidemic development curve under different incubation periods.

(A) The time-varying curves of the cumulative number of confirmed cases. (B) The time-varying curves of the cumulative number of the number of newly confirmed cases. (C) The time-varying curves of the cumulative number of the number of inpatient cases.(D) The time-varying curves of the cumulative number of the daily effective reproductive number. The data for each curve is the average of 10 simulations. The epidemic peak values increased and their corresponding dates delayed with the increase in the incubation period.

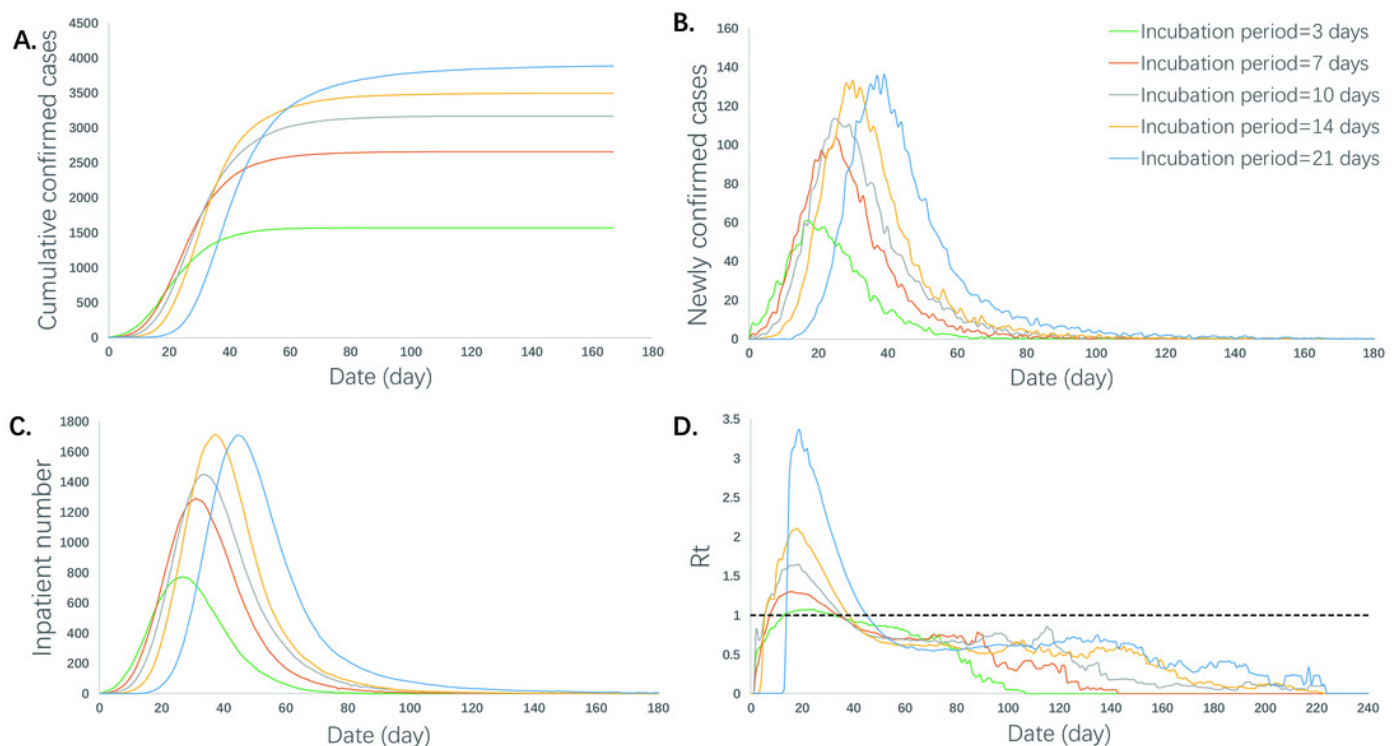



Figure 3

Epidemic development curve under different hospital response time

(A) The time-varying curves of the cumulative number of confirmed cases. (B) The time-varying curves of the cumulative number of the number of newly confirmed cases. (C) The time-varying curves of the cumulative number of the number of inpatient cases.(D) The time-varying curves of the cumulative number of the daily effective reproductive number. The data for each curve is the average of 10 simulations. The hospital's slow response speed caused an increase in the epidemic scale and a delay in the peak of the outbreak.

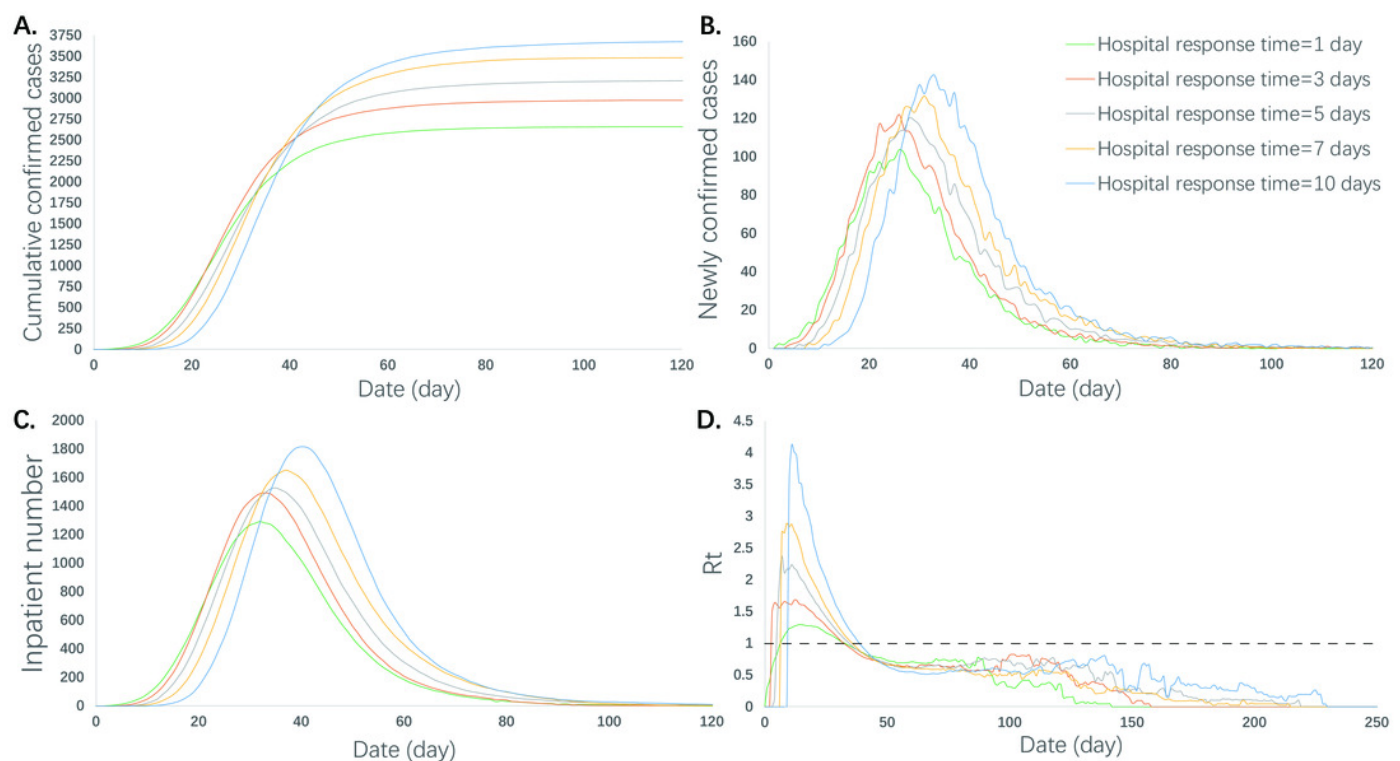



Figure 4

Epidemic development curve under different healing time.

(A) The time-varying curves of the cumulative number of confirmed cases. (B) The time-varying curves of the cumulative number of the number of newly confirmed cases. (C) The time-varying curves of the cumulative number of the number of inpatient cases. (D) The time-varying curves of the cumulative number of the daily effective reproductive number. The data for each curve is the average of 10 simulations. In this model, the ability of hospital treatment had no effect on the number of cumulative and newly confirmed cases. But the maximum number of inpatients increased and its corresponding peak dates delayed with the extension of the healing time.

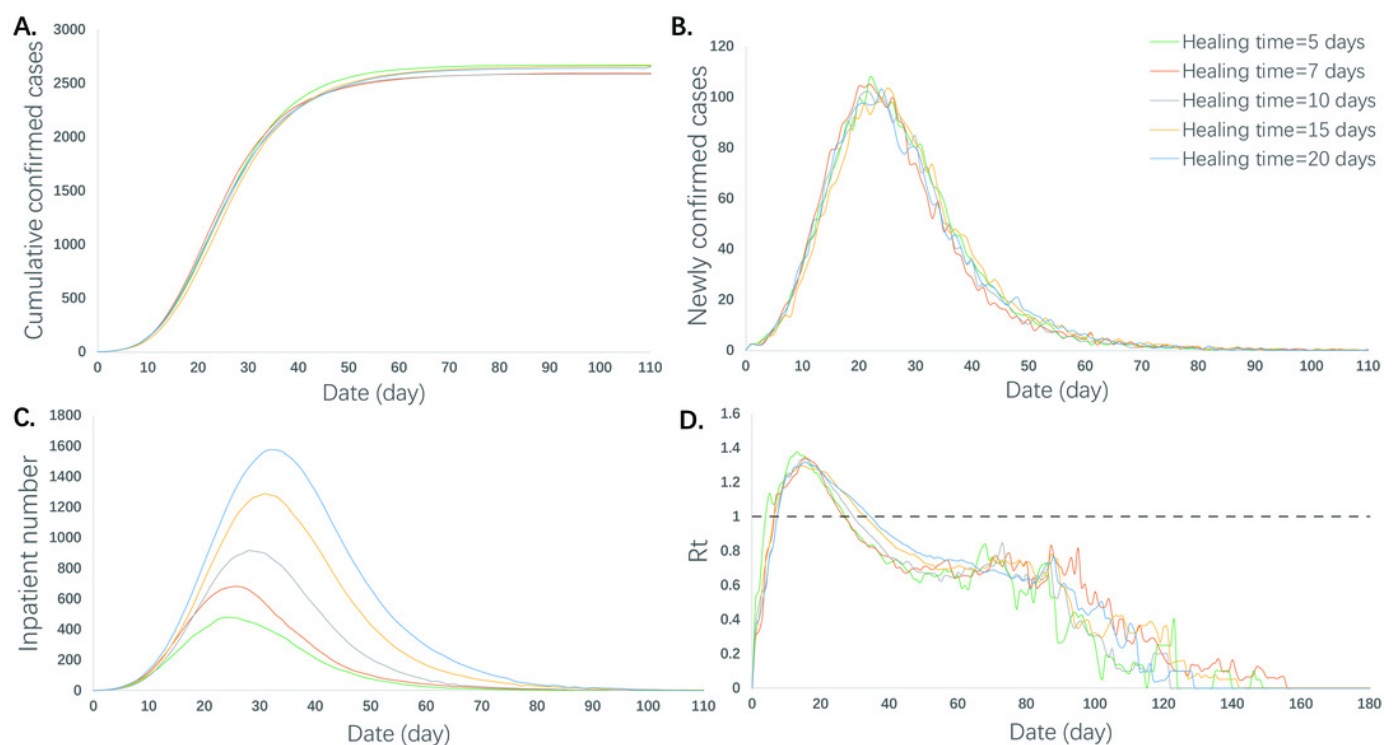



Figure 5

Epidemic development curve under different population mobility rates.

(A) The time-varying curves of the cumulative number of confirmed cases. (B) The time-varying curves of the cumulative number of the number of newly confirmed cases. (C) The time-varying curves of the cumulative number of the number of inpatient cases. (D) The time-varying curves of the cumulative number of the daily effective reproductive number. The data for each curve is the average of 10 simulations. Restrictions on population mobility made the peak number of cumulative confirmed cases, newly confirmed cases, and inpatient cases decreased. Population mobility rate had no effect on the value of Rt. However, the different transmission laws are displayed in extreme cases.

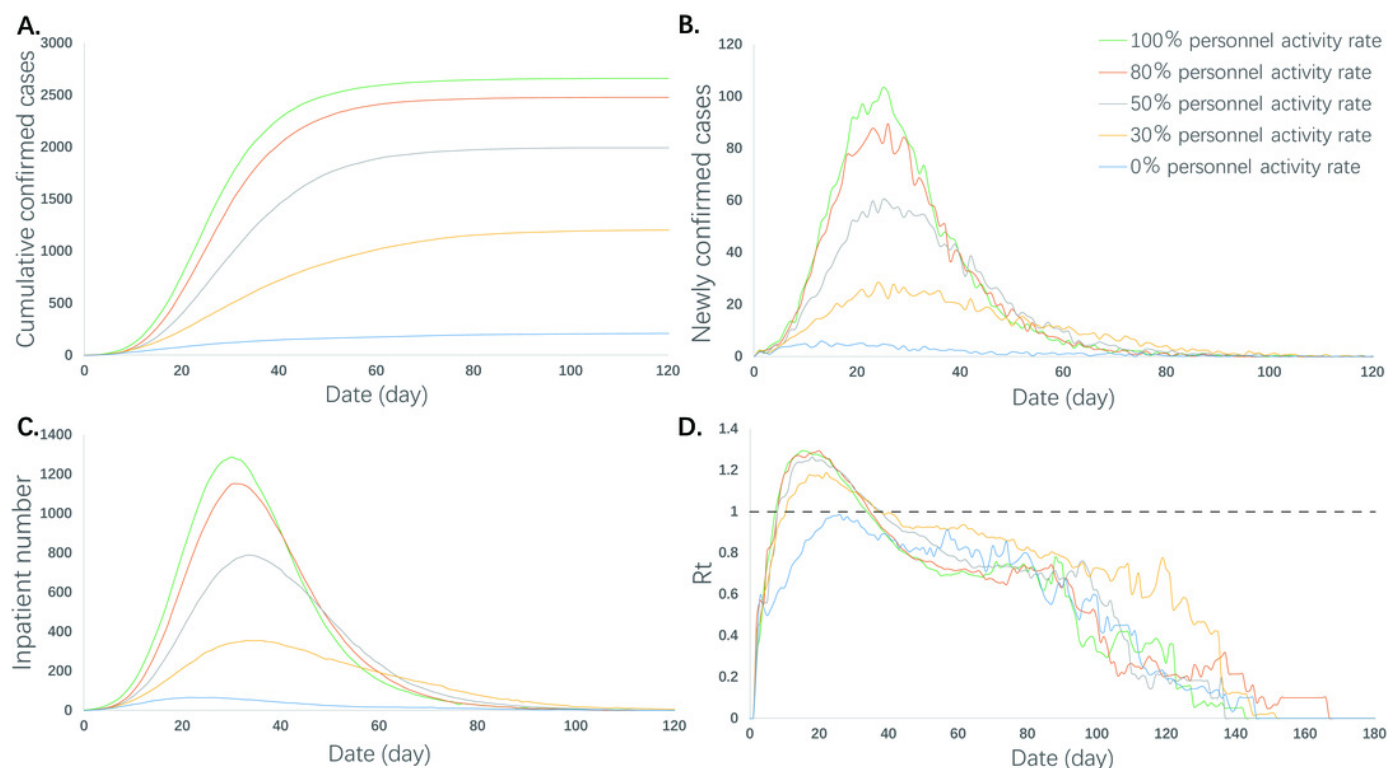



Figure 6

Epidemic development curve under different hospital isolation capacities.

(A) The time-varying curves of the cumulative number of confirmed cases. (B) The time-varying curves of the cumulative number of the number of newly confirmed cases. (C) The time-varying curves of the cumulative number of the number of inpatient cases.(D) The time-varying curves of the cumulative number of the daily effective reproductive number. The data for each curve is the average of 10 simulations. The peak number of cumulative confirmed cases and inpatient cases increased with the decrease in the isolation capacity. In addition, with the decrease in isolation capacity, the corresponding date of the peak inpatient number was delayed and the duration of isolation facilities at their full capacity increased. Isolation capacity had no effect on the newly confirmed cases and the value of Rt.

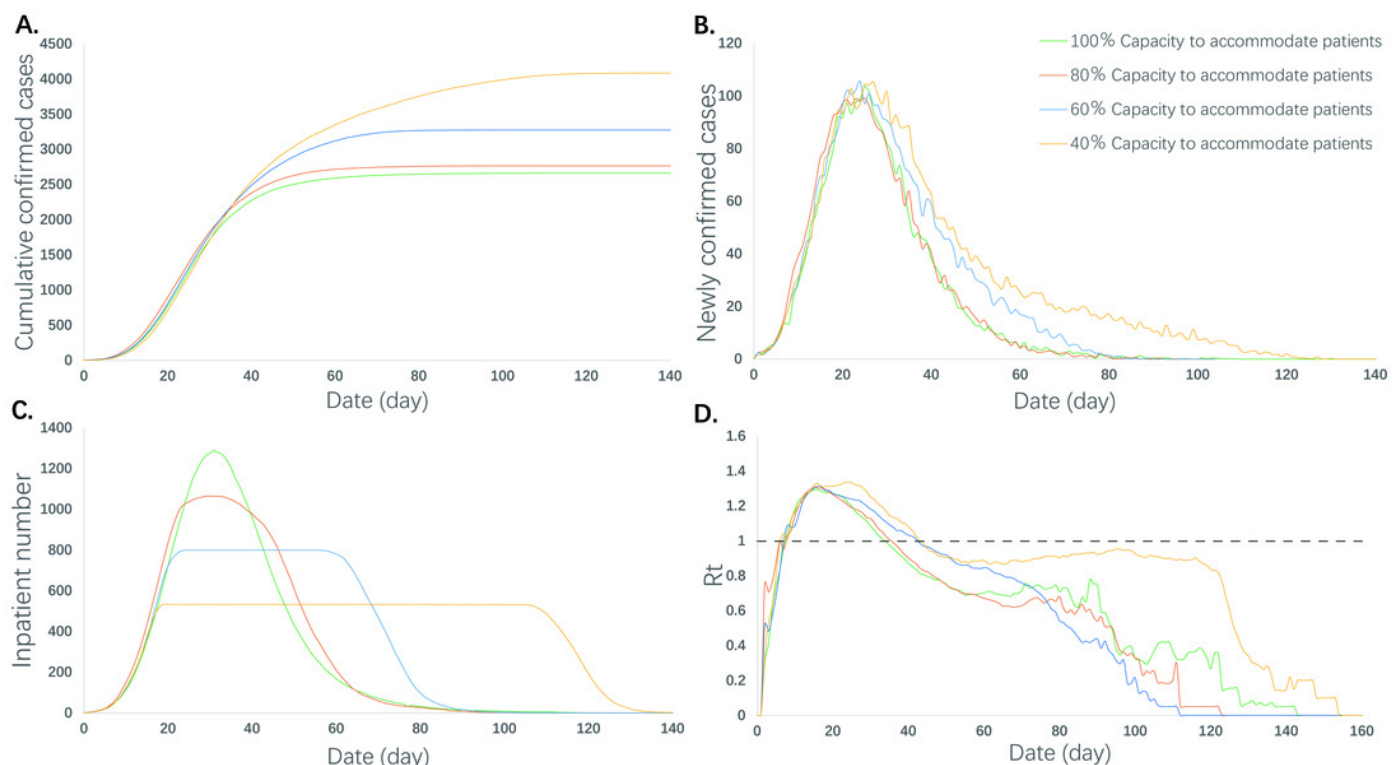
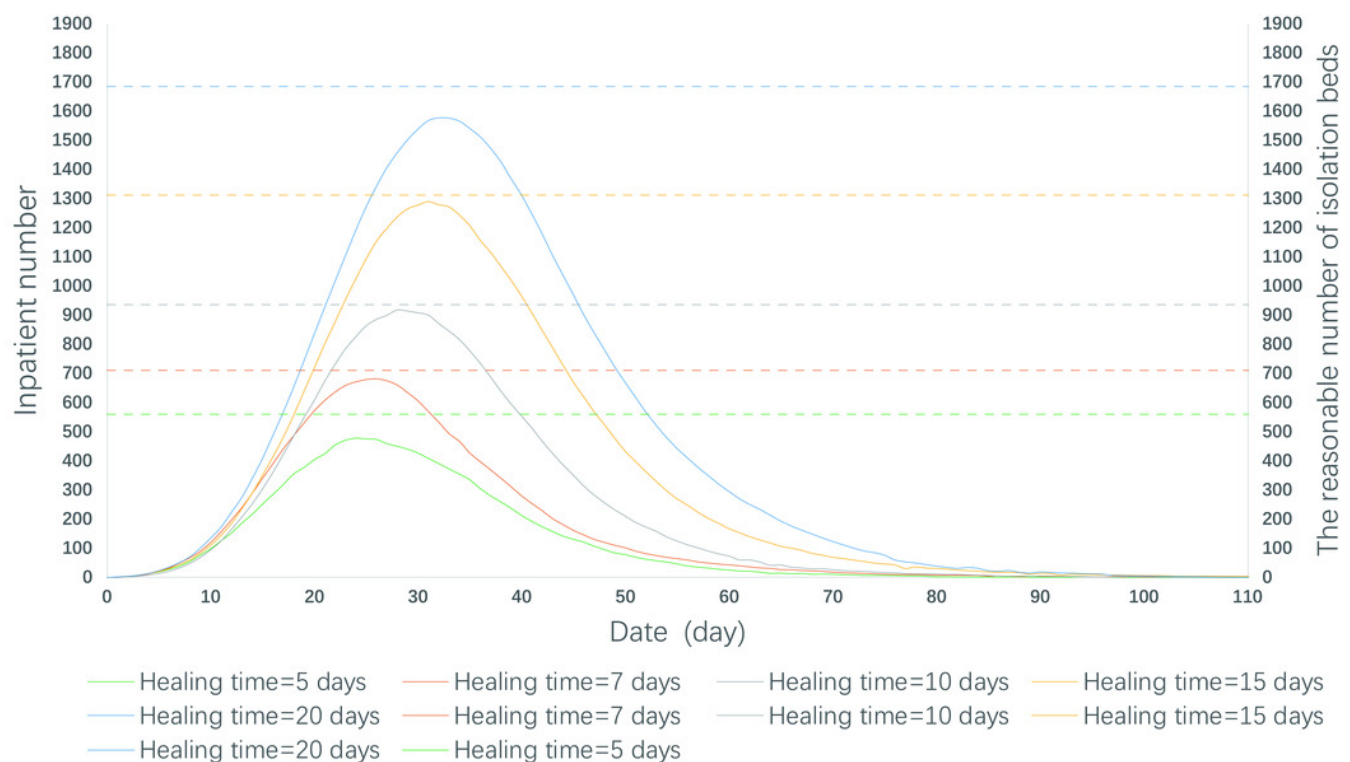



Figure 7

Prediction of a reasonable number of isolation beds in different healing times.

The solid line represents the time-varying curves of the number of inpatient cases at different healing times; the dotted line represents the reasonable number of isolation beds at different healing times.

Epidemic indicators under different incubation periods

a-There is a significant difference compared with group 1 ($p < 0.05$); b-there is a significant difference compared with group 2 ($p < 0.05$); c-there is a significant difference compared with group 3 ($p < 0.05$); d-there is a significant difference compared with group 4 ($p < 0.05$); e-there is a significant difference compared with group 5 ($p < 0.05$).

Group	Incubation period	Maximum newly confirmed cases		Maximum cases in incubation period		Maximum daily effective reproductive number	Sum of infected cases	Duration of the epidemic	Maximum inpatient cases	
		Number	Date	Number	Date				Number	Date
1	3	74[bcde]	19[bcde]	271[bcde]	17[bcde]	1.14[bcde]	1572[bcde]	87[bcde]	786[bcde]	26[bcde]
2	7	113[ade]	24[acde]	774[acde]	20[ae]	1.50[ade]	2660[acde]	114[ade]	1297[acde]	31[acde]
3	10	128[ade]	27[abe]	1192[abde]	21[ae]	1.78[ade]	3146[abde]	135[ad]	1475[abde]	34[abde]
4	14	147[abc]	30[abe]	1790[abce]	22[ae]	2.30[abce]	3518[abce]	164[ab]	1675[abc]	37[abce]
5	21	148[abc]	36[abcd]	2436[abcd]	26[abcd]	3.82[abcd]	3901[abcd]	202[abc]	1722[abc]	45[abcd]

Epidemic indicators under different hospital response times

a-There is a significant difference compared with group 1 (p<0.05); b-there is a significant difference compared with group 2 (p<0.05); c-there is a significant difference compared with group 3 (p<0.05); d-there is a significant difference compared with group 4 (p<0.05); e-there is a significant difference compared with group 5 (p<0.05).

Group	Hospital response time	Maximum newly confirmed cases		Maximum cases in incubation period		Maximum daily effective reproductive number	Sum of infected cases	Duration of the epidemic	Maximum inpatient cases	
		Number	Date	Number	Date				Number	Date
1	1	113[bcde]	24[cde]	774[bcde]	20	1.50[bcde]	2660[bcde]	114[ce]	1297[bcde]	31[cde]
2	3	131[ade]	25[cde]	935[ae]	19	2.06[acde]	2985[acde]	134[e]	1508[ade]	32[de]
3	5	133[ade]	27[ae]	945[ae]	19	2.80[abe]	3213[abde]	155[a]	1555[ade]	35[ae]
4	7	146[abc]	29[abce]	1010[ae]	18	3.27[abe]	3469[abce]	136[e]	1701[abc]	36[abe]
5	10	155[abc]	32[abcd]	1110[abcd]	19	4.98[abcd]	3695[abcd]	181[abd]	1802[abc]	39[abcd]

Epidemic indicators under different healing times

a-There is a significant difference compared with group 1 ($p < 0.05$); b-there is a significant difference compared with group 2 ($p < 0.05$); c-there is a significant difference compared with group 3 ($p < 0.05$); d-there is a significant difference compared with group 4 ($p < 0.05$); e-there is a significant difference compared with group 5 ($p < 0.05$).

Group	Healing time	Maximum newly confirmed cases		Maximum cases in incubation period		Maximum daily effective reproductive number	Sum of infected cases	Duration of the epidemic	Maximum inpatient cases	
		Number	Date	Number	Date				Number	Date
1	5	114	22	798	19	1.86[cde]	2677	95	493[bcde]	24[cde]
2	7	117	24	834	18	1.74[ce]	2603	113	694[acde]	26[ce]
3	10	111	23	792	19	1.38[ab]	2591	104	942[abde]	28[ab]
4	15	113	24	774	20	1.50[a]	2660	114	1297[abce]	31[a]
5	20	112	23	777	18	1.36[ab]	2643	108	1590[abcd]	33[ab]

Epidemic indicators under different population mobility rates

a-There is a significant difference compared with group 1 ($p<0.05$); b-there is a significant difference compared with group 2 ($p<0.05$); c-there is a significant difference compared with group 3 ($p<0.05$); d-there is a significant difference compared with group 4 ($p<0.05$); e-there is a significant difference compared with group 5 ($p<0.05$).

Group	Population mobility rate	Maximum newly confirmed cases		Maximum cases in incubation period		Maximum daily effective reproductive number	Sum of infected cases	Duration of the epidemic	Maximum inpatient cases	
		Number	Date	Number	Date				Number	Date
1	100%	113[cde]	24	774[cde]	20[e]	1.50	2660[bcde]	114	1297[cde]	31[e]
2	80%	98[cde]	23	681[cde]	20[e]	1.40	2477[acde]	117	1165[cde]	31
3	50%	70[abde]	25	456[abde]	22[e]	1.33	1994[abde]	119	799[abde]	34[e]
4	30%	34[abce]	26	203[abce]	23[e]	1.55	1204[abce]	133	368[abce]	35[e]
5	0%	9[abcd]	17	43[abcd]	11[abcd]	1.26	209[abcd]	108	74[abcd]	24[acd]

Epidemic indicators under different hospital isolation capacities

a-There is a significant difference compared with group 1 (p<0.05); b-there is a significant difference compared with group 2 (p<0.05); c-there is a significant difference compared with group 3 (p<0.05); d-there is a significant difference compared with group 4 (p<0.05); e-there is a significant difference compared with group 5 (p<0.05).

Group	Hospital isolation capacity	Maximum newly confirmed cases		Maximum cases in incubation period		Maximum daily effective reproductive number	Sum of infected cases	Duration of the epidemic	Duration of isolation facilities at full load *	Peak admission date
		Number	Date	Number	Date					
1	40%	119	25[c]	793	23[bcd]	1.40	4089[bcd]	143[bcd]	82[bcd]	18[bcd]
2	60%	115	24[c]	794	19[a]	1.34	3275[acd]	103[a]	34[acd]	22[acd]
3	80%	114	22[ab]	802	18[a]	1.37	2769[ab]	105[a]	13[abd]	25[abd]
4	100%	113	24	774	20[a]	1.50	2660[ab]	114[a]	0[abc]	31[abc]

Multiple-linear regression analysis of the reasonable number of isolation beds

**p<0.01

The table lists the results of the t-test and its P-value, indicating whether independent variables have a significant influence on dependent variables. The standard expression coefficient reflects the influence degree of each independent variable on the dependent variable after eliminating the influence of the dependent variable and the unit taken by the independent variable.

Independent variables	Regression coefficient	Standard regression coefficient	t	P
Constant	-0.273		-15.226	0.000**
Incubation period	0.009	0.302	10.276	0.000**
Population mobility rate	0.234	0.629	21.046	0.000**
Hospital response time	0.012	0.274	9.178	0.000**
Healing time	0.015	0.452	15.376	0.000**