Sg2 COVID-19 Surge Demand Calculator Overview and Methodologies

About the Calculator

The Sg2 COVID-19 Surge Demand Calculator provides a data-driven scenario planning tool for COVID-19 non-ICU bed, ICU bed and ventilator demand. The calculator design allows users to model COVID-19 inpatient demand and surge impact across local populations and to apply capacity considerations for regional market, health system or hospital planning.

In response to the increases in COVID-19 cases across the nation, Sg2 updated the Surge Demand Calculator, which incorporates additional opportunties to change the reproductive rate (R_0) and adjustable variables to model multiple viral spread scenarios in order to more accurately model local market second and third waves' impact on inpatient demand. This updated calculator version now also allows for additional inputs to scenario model the resurgence of COVID-19 based on changes in viral transmission rates and social distancing measure over time. In addition, the updated calculator allows users to model using an adjusted population, multiple hospitalization rates and secondary ALOS rates and to consider the impact of potential COVID-19 reinfection.

Use this calculator to:

- Identify where the market is on the timeline of the COVID-19 infection outbreak based on first-known community-acquired COVID-19 hospitalization date. Organizational COVID-19 average daily census (ADC) trends and patterns of increase can also be used to validate/adjust timing on the surge curve.
- Understand the impact of varying rates of disease spread, including scenarios that consider various social distancing efforts.
- Localize impact to reflect service area demographics via age-adjusted, COVID-19–infected, population-based hospitalization rates with the potential to incorporate in-migration to or out-migration from the region.
- Calculate and evaluate projected COVID-19 surge bed, ICU and ventilator shortage/surplus at the regional market, health system or organizational level.
- Assess multiple scenarios of resurgence based on changes in social distancing initiatives.
- Track shortage/surplus projections over time as disease transmission and market response progress.

What Input Data Are Requested

- Market demographics by age cohort
- Organizational market share
- Date of first-known local COVID-19 community-acquired hospitalization
- Local social distancing practice(s), date(s) enacted and date(s) rescinded
- Number of non-ICU beds, ICU beds and ventilators
- Non-ICU and ICU occupancy rates, ventilator availability

What Data Selections Are Requested

- Local initial infection rate (R_0) using suggested range
- Estimated social distancing adherence using suggested range
- COVID-19 hospitalization rate using suggested range
- COVID non-ICU, ICU and ventilator ALOS using suggested values
- COVID-19 ventilator/ICU ratio using suggested values

Additional Considerations

- This calculator models COVID-19 surge impact for inpatient non-ICU, ICU and ventilator demand only. Impact on other inpatient-related services, such as extracorporeal membrane oxygenation, and impact on outpatient services are not calculated at this time.
- This calculator assesses non-ICU, ICU and ventilator shortage/surplus based on user inputs of current bed and ventilator counts and occupancy rates. Entering supply and occupancy rate information will project total COVID-19 surge shortage/surplus. Changing inputs to reflect added or reduced capacity (eg, opening of flex space, decanting of elective and non–COVID-19 occupancy, reflecting staff shortages impacting actual staffed bed numbers) will adjust projections to reflect local, evolving shortage/surplus metrics.

Understanding Modeling Considerations for COVID-19 Surge Demand

There are many complex influences on COVID-19 impact modeling. However, understanding and accounting for key unknowns that affect COVID-19–related demand result in informed scenario planning.

What are these important unknowns, and why do they matter?

COVID-19 Reproductive Rates

How fast a disease moves through a population is an important consideration for how many related hospitalizations will occur and when. Early international data provided reference R values, or reproduction numbers, of between 2.4 and 2.6 in cities where outbreaks were severe. Over the course of the pandemic, we have observed the decline in R values with effective social distancing, lower population density and seasonal variation. Using these reference R values and other emerging disease benchmarks, established epidemiologic models known as susceptible-infected-recovered (SIR) models can be used to project how many people become infected and how rapidly these infections move through a population. Knowing these infected population details is the starting point for calculating how COVID-19 hospital demand will change over time.

Especially in the early stages of a novel disease, R values can change across geographies and time, making real-time modeling difficult. National and regional population density and factors such as multigenerational living behaviors can produce different R values for the same disease across different populations—making international R values difficult to apply universally. Adoption of transmission mitigation and containment strategies, accelerated disease surveillance and testing programs, and active contact tracing and quarantine processes can all influence how an R value changes in the same population over time, requiring modeling the fluctuation of R values over time to more accurately predict future surge(s).

To account for these complexities, the Sg2 COVID-19 Surge Demand Calculator provides the opportunity to select from a range of initial reproduction rates to account for changes in initial viral infection spread due to local factors. Sg2 has performed robust testing of R_0 inputs to this calculator using COVID-19 hospitalization trend data from early US COVID-19 market experience. This testing points to a limited range of R_0 values that produce the growth rates of COVID-19 hospital demand observed in both urban and rural US epicenters. This recommended range has been updated using the latest available hospitalization trend data and is detailed below.

Table 1. Sg2 COVID-19 Surge Demand Calculator Starting Infection Rate (Reproduction Rate, R_0) for Local Community Viral Spread: Reproduction Rates and Suggested Uses

R_0	2.5	2.4	2.3	2.2	2.1	2.0	1.9	1.8	1.7	1.6	1.5
Total Infection Rate (%)	91%	90%	89%	87%	85%	83%	77%	73%	70%	67%	64%
Relative Population Density	High urban density					Moderate urban density (urban/suburban mix)			Low urban density (rural)		
Relative Use of Public Transportation	High reliance on public transportation					Increased reliance on automobile transportation			No real public transportation use		

Note: R = reproduction number, a mathematical term that indicates how contagious an infectious disease is (R_0 or R naught). The total infection rate assumes no change in reproductive rate for the duration of the pandemic.

This calculator also allows for the modeled application of social distancing practices and their impact on reducing the rate of this disease spread. Specific disease suppression and containment strategies (eg, mask mandates, bans on large gatherings, hospitality industry closures, school closures, enforced shelter-in-place directives) have demonstrated the potential to significanlty reduce the strength and speed of COVID-19 spread in early outbreak communities. Aggressive testing, contact tracing and select isolation programs have also shown to effectively control the spread by bringing the transmission rate to suppression levels (reproduction number below 1.0).

The calculator provides the abilty to model the impact of local changes and fluctuations in social distancing measures over the longer-term course of the pandemic. Such changes may include the initiation of large gathering bans, mask mandates, school closures and nonessential business closures as well as impact events such as celebrations for statutory holidays and school reopening. Local population behavior changes, such as relaxation of and nonadherence to social distance measures, may also be seen. Modeling local reproduction rates in a given market over time can be fine-tuned to align with actual, observed hospitalization trends. Incorporating actual values for daily ADC is enabled in the row below the ADC projection outputs and can be used to pressure test modeling assumptions and narrow the range of potential transmission rates. To that end, the latest updates to the calculator allow users to enter up to 30 changes in the reproductive rate.

It should be noted that epidemiologic modeling demonstrates that, as you reduce an R value—thus reducing the strength of disease transmission—you also elongate the transmission period. As data from the COVID-19 pandemic continue to be gathered, updates to this calculator will reflect the best available epidemiologic data.

When translating disease transmission patterns to health care utilization, it is important to note that there is a lagging effect in terms of when a population becomes infected with disease and when they seek care because of that disease. In the case of COVID-19, it is estimated that new infections can take anywhere from 1 to 2 weeks or more to “wash through” the health care system. Similarly, it should be noted that social distancing practices typically take ~10–12 days to reduce novel coronavirus infection rates, and another ~4–7 days to begin to reduce hospital demand. In total, Sg2 has assessed that social distancing measures are not expected to “bend” local hospitalization demand curves for the first 14 days or more that they are in place. Sg2 has also run scenario modeling tests with early COVID-19 US market data and found that markets that enact social distancing within 14 days of their first community-acquired COVID-19 hospitalization have the best chance of containing true COVID-19 demand surge. The rate at which social distancing measures are gradually relaxed will be highly market-dependent, and little empirical evidence is currently available in terms of leading practice. It is assumed that if relaxation of social distancing measures produces untenable rates of growth in local infections, social distancing policies would be reinstated and would follow the same delayed impact patterns described above. Graphical elements in the Sg2 COVID-19 Surge Demand Calculator have been provided to help visualize the delay between infected population growth and resulting growth in hospital demand. For scenario planning, it is critical to remember that you must plan ahead for the future hospital demand that will be needed by the infected population already existing in your population.

Source: Chu DK et al. Physical distancing, face masks, and eye protection to prevent person-to-person transmission of SARS-CoV-2 and COVID-19: a systematic review and meta-analysis.*Lancet*. 2020;395(10242):1973–1987.

COVID-19 Running Percentage of Total Infected Population

The Sg2 Surge Demand Calculator includes a row on the Calculator Outputs Daily and Calculator Outputs Weekly tabs that report the SIR model calculations for the running percentage of the total infected population over time. The SIR model calculates a daily count for susceptible, infected and recovered for severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) infection for a given population. In doing so, the infected population rate can be derived as the cumulative total infected population over the total population. It is important to note that the tally of total infected adjusts the total susceptible counts in a 1-to-1 fashion. Over time, as the total infected population rises, it modestly impacts the transmission rate of new infections, because the susceptible population is gradually decreasing. In markets with total infection rates greater than 30%, it takes a higher R_0 value to maintain the same rate of transmission. Scenario model testing has demonstrated that markets with large, primary surges (>100% ICU occupancy for >2 weeks) have lower likelihood of a secondary surge that would surpass prior peak bed demand. Markets that did not experience a large, primary surge, however, are at increased risk of a second surge that is larger in peak ADC than the first.

Validation of the SIR calculations for running percentage of total infected population has been performed and found to align with seroprevalence data in New York City, NY; Chicago, IL; and San Francisco, CA. For example, several published seroprevalence studies from New York City reported similar SARS-CoV-2 antibody prevalence rates, between 20.0% and 22.7% antibody positivity for SARS-CoV-2 for the time frame of April 19–28, 2020. For this same time frame, the SIR model calculates the total running infection rate for New York City to be 21.9% on April 19 and increasing to 24.5% on April 28. Comparing market seroprevalence data for specific dates with the SIR calculations has been shown to align closely when using seroprevalence data specific to a market and not a larger region (eg, state) where blended immunity rates over a large geography (rural, subruban and urban) lack specificity for the target marget. In addition, alignment of infection and seroprevalence positivity rates align more closely when using an initial hospitalization rate between 1.2% and 1.6%. For the New York City validation analyis, the hospitalization rate used was 1.6%. Hospitalization rates less than 1% generated higher SIR running totals for infected populations. In addition, there is the possibility that published seroprevalence studies modestly underestimate the true infected population due to false negatives and waning of antibodies over time in some individuals with documented positive viral tests for SARS-CoV-2. This analysis is ongoing and dependent on release of seroprevalence population-based data available.

Sources: Stadlbauer D et al. Repeated cross-sectional sero-monitoring of SARS-CoV-2 in New York City. *Nature*. November 2, 2020; Rosenberg ES et al. Cumulative incidence and diagnosis of SARS-CoV-2 infection in New York. *Ann Epidemiol*. 2020;48:23–

29.e4; Anand S et al. Prevalence of SARS-CoV-2 antibodies in a large nationwide sample of patients on dialysis in the USA: a cross-sectional study. *Lancet*. 2020;396(10259):1335–1344.

COVID-19 Hospitalization Rates

At the beginning of the pandemic, the literature cited COVID-19 hospitalization rates from international data that used positive COVID-19 test case volumes in the denominator. These rates use the number of COVID-19 admissions as the numerator and the number of positively tested COVID-19 cases as the denominator. Because of a lack of COVID-19 testing in the total underlying population, these positive test case rates are the only hospitalization data available early in the COVID-19 pandemic outbreak. These positive-case–based rates are an important metric in understanding the impact of COVID-19, but they should NOT be confused with population-based COVID-19 hospitalization rates. Population-based COVID-19 hospitalization rates use the number of COVID-19 admissions as the numerator and the number of total population infections as the denominator. Because of a lack of testing, the challenge has been in having a reliable denominator that represents the true infected population.

To solve for these challenges, Sg2 used international data to calculate a reasonable population-based COVID-19 admission rate. Using data from Lombardy, Italy, that detailed the COVID-19 experience (including local population numbers, reported ICU rates for COVID-19 hospitalizations, reported ICU COVID-19 average daily census by date and reported first COVID-19 ICU admissions by date) and that applied an assumed disease transmission rate of R 2.4, Sg2 extrapolated the true infected population numbers under the SIR curve for these inputs and derived a population-based COVID-19 admission rate of 1.2%. This calculated population-based admission rate was then rechecked against COVID-19 case volumes and bed surge numbers reported out of the Lombardy region, verifying that calculated COVID-19 admission rates hold true to observed patterns seen in Italy in early data. Sg2 has also tested the hospital rate against early data from New York City, Chicago, San Francisco, and Albany, GA. In all cases, hospitalization rates ranging from 1.0% to 1.6% have coincided with observed COVID-19 hospitalization volumes.

Additionally, it is important to consider that COVID-19 appears to have varying impacts on hospitalization rates by age and possibly by specific comorbidities. To account for this, Sg2 has applied age adjustments to hospitalization rates and critical care (ICU) utilization rates per age-adjusted COVID-19 data reported out of Italy. In addition, updates to the calculator allow users to utilize up to 3 different hospitalization rates to account for the changes in infection spread patterns throughout the progression of the disease.

COVID-19 ICU and Ventilator Rates

Practice patterns for treatment of COVID-19 cases vary by hospital and result in differences in the percentage admitted requiring the ICU or a ventilator. The user is encouraged to input their local ICU and ventilator percentages to more accurately predict future demand. Sg2 has observed a significant reduction in the percentage of patients hospitalized requiring the ICU or ventilation over the course of the pandemic as a result of clincial advances in treatment. An updated feature in the v6.1 calcualtor is the abilty to input a secondary, later, percent ICU and percent ventilator to reflect important changes in utilization that impact average daily census projections.

This calculator allows for up to 2 user-defined rates of critical care (ICU) need in a COVID-19 hospitalized population. The following reference value can assist a user in their input selection to the model.

- **30% =** the conservative estimate recommended by the CDC during initial phase of pandemic.
- **25% =** Sg2's recommended selection, as observed in early hospitalization data of US epicenters, with the understanding that disease severity and practice patterns are yet unknown in the US.
- **16% =** published rate of critical care (ICU) need in a COVID-19 population, Lombardy, Italy. It should be noted that data from the Lombardy region show that COVID-19 ICU rate ranged from 27% in the early outbreak to 11% near peak demand and was likely influenced by a lack of local ICU bed availability.
- Sg2 has observed a wide variation in US hospitals' ICU rates, ranging from 15% to 50% hospitalized requiring the ICU. This rate has decreased over the course of the pandemic for all hospitals observed.

Source: Grasselli G et al. Critical care utilization for the COVID-19 outbreak in Lombardy, Italy: early experience and forecast during an emergency response. JAMA Network. March 13, 2020.

Additionally, this calculator allows for up to 2 user-defined rates of mechanical ventilation in the critical care (ICU) COVID-19 hospitalized population. The following reference values can assist a user in their input selection to the model.

- Current data from New York City's COVID-19 experience indicate that 80% to 90% of COVID-19 ICU patients require ventilator care.
- Reports from Seattle, WA, indicate that ~75% of COVID-19 ICU patients were placed on mechanical ventilation.
- Early reports from US hospitals along the West Coast indicate that approximately 2 out of 3 COVID-19 ICU patients require ventilator care.
- Clinical advances and better understanding of risk factors for respiratory failure have led to a significant decline in ventilation use for hospitalized patients. The above rates were reported during the early pandemic and have subsequently decreased over the course of the pandemic. Sg2 encourages modeling local hospital practice pattern rates for this input.

COVID-19 ALOS

Planning for COVID-19 surge capacity involves not only an understanding of disease spread and a realistic evaluation of hospitalization rate but also a reasonable reference for COVID-19 average length of stay. Sg2's COVID-19 Surge Demand Calculator provides a range of selectable ALOS values for modeling purposes, anchored around published COVID-19 ALOS from international experience. As US practice patterns evolve for the care of COVID-19 patients, based on advances in treatment, the latest version of the calculator allows users to model secondary values for ALOS. Through selection of varying ALOS inputs, users can model how practice pattern shifts would impact capacity shortage/surplus projections. As organizational experience with treatment of a COVID-19 population grows, this local experiential evidence should drive both the initial and secondary calculator ALOS selections.

Reference data from Lombardy, Italy:

- 8 days non-ICU: ALOS reference value
- 6 days non-ICU, 10 days ICU: ICU ALOS reference values

  Source: Ferguson NM et al. Impact of non-pharmaceutical interventions (NPIs) to reduce COVID-19 mortality and healthcare demand. Imperial College COVID-19 Response Team. March 16, 2020.

- Reports from Seattle, WA, indicate that COVID-19 ALOS for critical patients is 9 days in the ICU.

  Source: UCSF School of Medicine. The epidemiology, science & clinical manifestations of COVID-19. A UCSF update [video]. April 2, 2020.

- Aggregate data collected by Strata from 85 health systems from across the nation suggest that the median COVID-19 ALOS typically ranges from about 7 to about 9.5 days. The ALOS increased from 7 to about 9.5 days between April and May, before decreasing to approximately 8 days between June and July, and once again increasing to about 9 days between July and August.

  Source: Strata Decision Technology [analytics platform], Chicago, IL.

The above rates were reported during the early pandemic and have been noted to significantly vary by hospital due to case mix and practice pattern differences. In addition, recent US hospital data suggest a decline in ALOS over the course of the pandemic. Sg2 encourages modeling local hospital practice pattern rates for this input.

COVID-19 Reinfection

Over the past few months, documented cases have emerged regarding COVID-19 reinfections. While national and international evidence is limited, the existing literature points to the direction of long-term immunity from SARS-CoV-2 infection among 90% of study participants who were found to have at least 3 out of 5 forms of immunity. Studies also show that documented cases of reinfection are rare and lower in acuity, and its onset takes place 6 months after the initial infection. While Sg2 experts recommend modeling without reinfections, the latest version of the calculator offers the capability for users to incorporate the *potential* impact of COVID-19 reinfections within the model.

Sources: Havers F et al. Seroprevalence of antibodies to SARS-CoV-2 in 10 sites in the United States, March 23–May 12, 2020. JAMA International Medicine Original Investigation. July 21, 2020; Poland G et al. SARS-CoV-2 immunity: review and applications to phase 3 vaccine candidate. *Lancet* 2020;396(10262):1595–1606; Dan J et al. Immunological memory to SARS-CoV-2 assessed for greater than six months after infection [preliminary report not peer-reviewed at time of publication of this document, preprint available]. BioRxiv. November 15, 2020.

Additional Modeling Considerations

As previously mentioned, users have the capability to model local reproductive rates over time based on actual hospitalization trends. In the Calculator Output tabs, there are “free text” rows below ADC projection outputs, which can be used to compare model outputs to actual hospitalization data by date. Updating the model frequently with the most current and latest hospitalization data can help users pressure test modeling assumptions, narrow the range of potential transmission rates and help ensure more accurate 2-week projections for planning purposes.

Methodology Details and Data Sources

The Sg2 COVID-19 Surge Demand Calculator's methodologies have been vetted by hospital systems, Vizient biostatisticians, and outside epidemiologic and pandemic experts. The following methodologic details are critical to understanding the calculator's approach. These methodologies will be updated as necessary, with forthcoming US data points and additional emerging COVID-19 information. Subsequent versions of this calculator will be released as COVID-19 understanding advances.

SIR Modeling Inputs

The calculator parameters allow for the incorporation of SIR models of COVID-19 disease spread, driven by reproduction rates available in a selectable range. Parameters driving modeling within the calculator are noted below.

Initial, selectable R_0 values: 3.0, 2.9, 2.8, 2.7, 2.6, 2.5, 2.4, 2.3, 2.2, 2.1, 2.0, 1.9, 1.8, 1.7, 1.6, 1.5

Time step: 1

Pre-infectious period (days): 5

Infectious period (days): 8

Sources: Ferguson NM et al. Impact of non-pharmaceutical interventions (NPIs) to reduce COVID-19 mortality and healthcare demand. Imperial College COVID-19 Response Team. March 16, 2020; McIntosh K et al. *Coronavirus Disease 2019 (COVID-19).* UpToDate. March 27, 2020.

When testing calculator outputs against the most recently available international and national COVID-19 hospital surge experience, Sg2 found that initial R_0 values between 2.5 and 1.5 are most indicative of the rates of growth of COVID-19 hospitalizations seen across urban, suburban and rural markets to date. After the introduction of social distancing measures, R values decrease to varying levels depending on the level of social distancing, with strict stay-at-home measures decreasing the R values over the span of 8 weeks to close to 1.0.

SIR modeling used in this calculator calculates beta as R_0 * Time step / (Infectious period * Total population). This beta is defined as the rate at which 2 individuals come into effective contact per time step—or as the rate of transmissibility of disease. The beta is modified each time a social distancing category is documented as being enacted at the local market level. This modification reduces the beta by the mitigation magnitude input by the user, effectively reducing the infection rate by reducing the transmissibility of disease. Beta reduction for initial social distancing practices such as large gathering bans, school closures and nonessential business closures is set to –20% of beta. Beta reductions for more elevated social distancing practices such as stay-at-home bans are set to a total reduction of –50% of beta. In all instances of the reduction in beta, the number of days before this reduction takes effect is equal to the user input of "Time between social distancing practices enacted and impact on health system demand (days)" minus the days estimated between social distancing impact and hospitalization impact (set as a default of 5 days in this model). The "Time between social distancing practices enacted and impact on health system demand (days)" input parameters for this model allow for user entry of 13 to 17 days.

Many resources on US social distancing policies, timing and adherence are publicly available. Sg2 recommends:

https://www.kff.org/health-costs/issue-brief/state-data-and-policy-actions-to-address-coronavirus/

https://www.google.com/covid19/mobility/

Increasingly, publicly available resources are available that calculate a changing R_0 relative to COVID-19. Sg2 recommends:

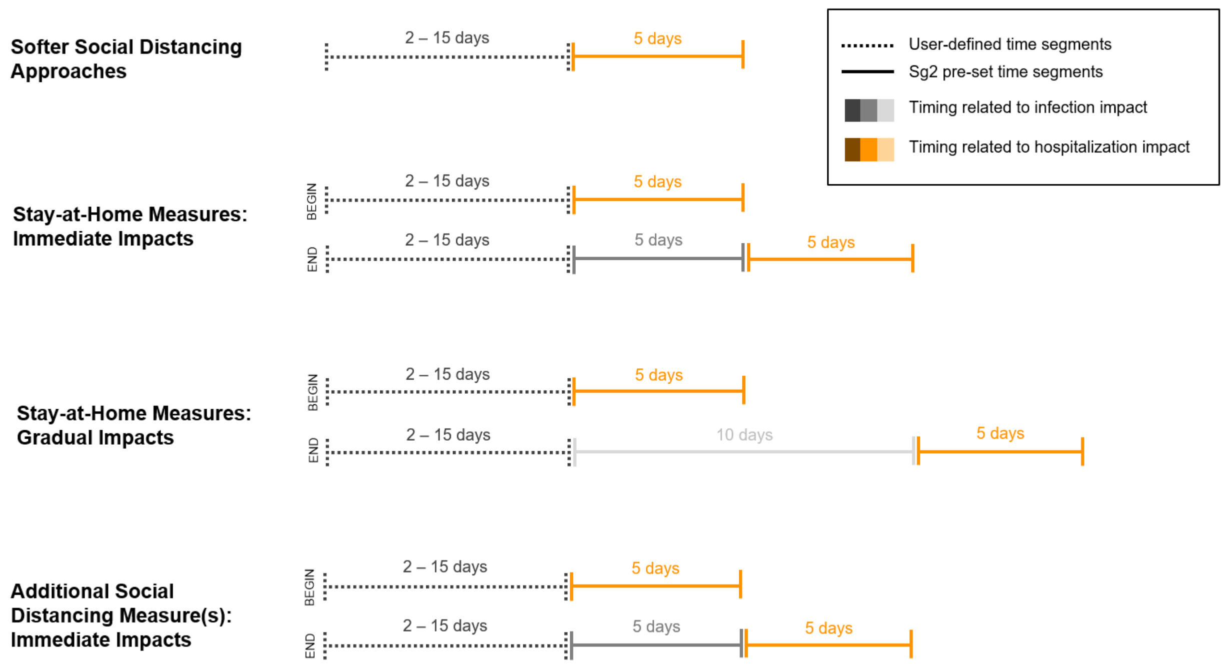
https://rt.live/

SIR modeling used in this calculator does not account for the potential reinfection of a recovered population by the same or a different strain of SARS-CoV-2. It is assumed that multiple strains of SARS-CoV-2 are currently involved in today's COVID-19 pandemic.

Social Distancing Impacts and Calculated Timing

Sequential social distancing impacts found within this calculator are now formulated as an additive sum. Previously, sequential social distancing impacts resulted in a total impact equal to the magnitude of the last social distancing impact input (previously the impact of stay-at-home order).

This calculator allows for the scenario modeling of various approaches to social distancing initiatives assumed to impact infection transmission rate. The timing of how social distancing inputs affect model outputs relates to both a social distancing initiative's impact on infection rate and the delayed impact on hospitalizations. Across the various social distancing scenarios allowed for in the calculator is a range of user-defined and Sg2 preset timing elements, described in the diagram below.



The above timing patterns, including the referenced "begin" and "end" dates, are put into context in the working model within the Scenario Dates tables included in the output tabs. These reference tables are useful guides for understanding the timing intervals described above at work in the active scenario model. Impact on the ADC will occur within 3 days of the R_0 being fully realized on the active infected population. For social distancing steps with overlapping dates, the impact of the later social distancing step will not begin until the impact of the prior social distancing step is fully realized.

SCENARIO DATES	Date Ro Change Begins: Date	Date Ro Change Begins: Running % of Total Population Infected	Date Ro Change is Fully Realized on Active Infected Population: Date	Date Ro Change is Fully Realized on Active Infected Population: Running % of Total Population Infected	Resulting Reproductive Rate (Ro)
First COVID-19 hospitalization	February 27, 2020	0.1%	-	-	Ro = 2.5
Initial social distances measures put into place	March 7, 2020	0.4%	March 18, 2020	2.7%	Ro = 2
Stay-At-Home Order: initial impact	March 22, 2020	4.5%	April 7, 2020	20.5%	Ro = 0.9
Stay-At-Home Order, additional: gradual impact	March 27, 2020	8.1%	April 17, 2020	25.1%	Ro = 0.6

SCENARIO 1

	Date Ro Change Begins: Date	Date Ro Change Begins: Running % of Total Population Infected	Date Ro Change is Fully Realized on Active Infected Population: Date	Date Ro Change is Fully Realized on Active Infected Population: Running % of Total Population Infected	Resulting Reproductive Rate (Ro)
1st additional change in Ro	April 1, 2020	13.8%	April 17, 2020	25.1%	Ro = 0.9
2nd additional change in Ro	April 15, 2020	24.4%	May 1, 2020	29.1%	Ro = 1.1
3rd additional change in Ro	May 1, 2020	29.1%	May 17, 2020	32.5%	Ro = 1.4
4th additional change in Ro	May 15, 2020	32.1%	May 31, 2020	35.2%	Ro = 1.6
5th additional change in Ro	June 1, 2020	35.4%	June 17, 2020	38.8%	Ro = 1.9
6th additional change in Ro	June 15, 2020	38.4%	July 1, 2020	42.5%	Ro = 1.6
7th additional change in Ro	July 1, 2020	42.5%	July 17, 2020	46.0%	Ro = 1.8
8th additional change in Ro	July 15, 2020	45.6%	July 31, 2020	48.7%	Ro = 1.9
9th additional change in Ro	August 1, 2020	48.8%	August 17, 2020	51.5%	Ro = 1.8
10th additional change in Ro	August 15, 2020	51.2%	August 31, 2020	53.2%	Ro = 1.6
11th additional change in Ro	September 1, 2020	53.3%	September 17, 2020	54.4%	Ro = 1.5
12th additional change in Ro	September 15, 2020	54.3%	October 1, 2020	54.9%	Ro = 1.6
13th additional change in Ro	October 1, 2020	54.9%	October 17, 2020	55.3%	Ro = 1.8
14th additional change in Ro	October 15, 2020	55.2%	October 31, 2020	55.5%	Ro = 1.9
15th additional change in Ro	November 1, 2020	55.5%	November 17, 2020	55.7%	Ro = 1.6
16th additional change in Ro					
17th additional change in Ro					
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BEGIN

END

These social distancing timing patterns were constructed based on observed, actual COVID-19 data trends from both Italy and New York, both of which have demonstrated an approximate 3-week delay from stay-at-home measure enactment to visible reduction in hospitalization demand. The timing patterns described above also allow for end-user flexibility in modeling the various local approaches to social distancing rollout, with the understanding that local market observed behaviors may be different than epicenter behaviors.

While the combination of social distancing impacts noted above are sequentially additive, the calculator does not allow for a calculated R_0 below 0.

Additionally, error messaging has been built into the calculator to guide users in appropriate input ranges for social distancing impacts within the input tab:

- If dates of social distancing measures are not in sequential order (eg, if additional change in social distancing measure is made prior to enactment of stay-at-home order), error message prompts correction.
- If social distancing measures populate an R_0 of below 0, error message prompts correction.

Hospitalization Rates

This calculator allows for entry of user-defined infected population hospitalization rates, with an acceptable range of 5% to 0.5% for scenario modeling purposes.

Sg2 recommends a hospitalization rate of 1.0% to 1.6% based on analysis of data and COVID-19 experience from Lombardy, Italy; New York City; San Francisco; Chicago; and Albany, GA. Data used by Sg2 for COVID-19 infected population hospitalization rate calculations include:

- February 20, 2020: first COVID-19 ICU admission
- March 11, 2020: 1,028 COVID-19 ICU beds in use
- Percentage of hospitalizations needing ICU care: 16%

Source: Grasselli G et al. Critical care utilization for the COVID-19 outbreak in Lombardy, Italy: early experience and forecast during an emergency response. JAMA Network. March 13, 2020.

- R 2.4 = rate of disease spread in Lombardy, Italy
  - Assumed based on reported R values from early disease spread in Wuhan, China
- 10,400,000 = conservative total population of Lombardy, Italy

Source: Lombardia. City population. Accessed March 2020.
Note: Modeling assumes March 11, 2020, equals Day 20 of disease transmission in Lombardy, Italy, as calculated from time of first ICU admission to time of ICU bed data reported. This assumption intentionally underestimates the pace of disease transmission—it is likely that disease transmission would have been occurring in the population before the first ICU admission, thus making the true date of first ICU admission Day 1+x. This intentional underestimate of disease burden calculates a slightly higher COVID-19 admission rate, ensuring that derived hospitalization rates do not underestimate hospital demand based on observed experience.

This calculator also includes age-adjusted hospitalization rates specific to COVID-19 experience from Italy. The following hospitalization data are used as a baseline for hospitalization rate multipliers at the age cohorts listed in Table 3 and requested in the calculator demographic inputs. The table interprets “symptomatic cases requiring hospitalization” to indicate COVID-19–positive hospitalized cases.

Table 3. Age-Adjusted Hospitalization Rate Reference Values Applied as Multipliers to Sg2 Overall Hospitalization Rate Selections

Age Group	% Symptomatic Cases Requiring Hospitalization	% Hospitalized Cases Requiring Critical Care
0 to 9	0.1%	5.0%
10 to 19	0.3%	5.0%
20 to 29	1.2%	5.0%
30 to 39	3.2%	5.0%
40 to 49	4.9%	6.3%
50 to 59	10.2%	12.2%
60 to 69	16.6%	27.4%
70 to 79	24.3%	43.2%
80+	27.3%	70.9%

Source: Ferguson NM et al. Impact of non-pharmaceutical interventions (NPIs) to reduce COVID-19 mortality and healthcare demand. Imperial College COVID-19 Response Team. March 16, 2020.

COVID-19 Reinfection

The latest version of the Sg2 COVID-19 Surge Demand Calculator allows users the option to incorporate the potential of COVID-19 reinfections. Evidence suggests that COVID-19 immunity exists for at least 8 months after initial infection. Should the user opt to use this functionality, the SIR model assumes that the average time for potential reinfections to occur will be 9 months after the initial infection. The average of 9 months is applied to a normalized distribution, where each standard deviation corresponds to 1 month.

Calculator Output Visualizations

Outputs of SIR modeling include daily time-step data aggregated to weekly summaries for the Calculator Outputs (Weekly) tab display. Current versions of this calculator have removed the timeline of first modeled infection to prevent confusion in the lagging timeline of hospitalization. All time references in the calculator relate to COVID-19 hospitalization demand.

The timing of modeled weeks/days since first hospitalization and the placement of calendar dates within the tool are anchored in the assignment of the user-input “date of first community-acquired COVID-19 hospitalization” to the first calculated full-integer COVID-19 hospitalization, seen as a product of underlying SIR modeling of infected population and user-selected COVID-19 hospitalization rate. In this way, the date assignment in the model is dependent on when modeling mechanics predict the first COVID-19 hospitalization to occur based on calculated growth in an underlying infected population and selected hospitalization rate. In this way, the placement of the user input date of first COVID-19 community-acquired hospitalization along the model trajectory is a function of both the selected COVID-19 hospitalization rate and the selected R_0.

Because of increased flexibility in user selection of R_0 values, this calculator no longer highlights the Output Week peak range by visual header (this will change with R_0 selection) and no longer provides an estimated range of COVID-19 ADC doubling rate by week interval in the Output Daily tab (this will also change with R_0 selection).

A single row of “free text” entry per output data set has been made available in the calculator design to accommodate user entry of actual organizational values for easy comparison to scenario model projections.

SIR model outputs connect directly to calculations of age-adjusted COVID-19 hospital admissions, ICU admissions and ventilator use, as well as ADC calculations for these categories. In these calculations, the appropriate age-adjusted hospitalization/use rate is applied to a calculated, age-distributed, infected population from 5 days prior to account for the delay in symptomatic presentation at the hospital.

In the Output Weekly tab, Week 1 is represented by identified first hospitalization date, divided by 7, rounded down, plus 1. The addition of 1 ensures that the round-down function always returns a positive integer value for Week count, and it creates alignment between Week 1 and Day 1 assignments in both output tabs of the calculator.

Weekly Output values represent the maximum weekly projected value of that week, not the average of the week. This methodological selection ensures alignment of data points between weekly and daily outputs.

In general, rounding has been applied to all values displayed for non-ICU average daily census, ICU ADC and ventilator ADC, as well as all related displayed values for shortage/surplus estimates. Rounding logic is as follows:

- If <100, no rounding.
- If <500, round to nearest 10.
- If <1,000, round to nearest 50—otherwise, round to nearest 100.

Rounding logic has been applied to give the user a projected target range for ADC and capacity shortage/surplus planning. In cases of small projected values, particularly for ventilator projections in small markets, rounding logic may produce the same week-over-week projected values. This is because the rounding function is applied at the age-specific ADC level, which can be a small value. Rounding of these small values and then summing across age groups can produce little projected growth/variation. This is an expected behavior of the model.

The “scenarios parameters” reference found within weekly and daily output tabs has been expanded to include a “scenario dates” section. This section includes reference values for the start and completion of modeled impacts and effective R_0 values across dates related to: first COVID-19 hospitalization; initial social distancing measures put into place; stay-at-home order: initial impact; stay-at-home order: additional, gradual impact; relaxation of social distancing measures; and reinstatement of social distancing measures.

Estimated day-over-day percentage of total population infected calculations based on underlying SIR modeling has been added along the running timeline in the daily output tab.
Output graphs have been reformatted to use projected calendar dates vs numbered days or weeks for better trend context.

The daily and weekly outputs have been updated to show projected trends out to 400 days; related tables and graphs have also been updated to show projections out to 400 days. Related graphs formatted to show tick marks every 2 weeks.

DISCLAIMER: Output from the Sg2 Surge Demand Calculator is not a final answer, but users should see it as a data point to incorporate into their broader planning process. Users must also remain committed to updating their inputs and regularly running scenarios. As organizations pursue scenario planning and consider options for combating bed shortages, Sg2 is prepared to help. Inputs and outputs for this tool are complex, and we have the resources to support careful use and results interpretation. Final prioritization and decisions, however, are solely the users’.