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Panalysis: A New Spreadsheet-Based Tool for Pandemic Planning

Mark N. Abramovich, Eric S. Toner, and Jason Matheny

Publicly available influenza modeling tools are of limited use to hospitals and local communities in planning for a severe pandemic. We developed Panalysis, a new tool to estimate the likely healthcare consequences of a pandemic and to aid hospitals in the development of mitigation and response strategies. By way of example, we demonstrate how Panalysis can be used to plan for a 1918-like flu pandemic. We discuss potential future applications of this tool.

Effective planning for an influenza pandemic at the hospital or community level requires the ability to project the impact of an outbreak on available local medical resources, such as inpatient hospital beds and mechanical ventilators. To make such projections, the planner must (1) make assumptions about the specific nature of the outbreak (e.g., attack rate, severity, duration, and epidemiologic curve), and (2) gather or estimate relevant information about the hospital's capacity, capabilities, and resources. Since the specifics of a future pandemic are unknown and could vary over a wide range, different scenarios must be considered. The projected number of patients must be matched, day-by-day or week-by-week, with the resources projected to be available. These projections require thousands of individual calculations. Therefore, effective planning is facilitated by use of a computerized modeling tool that can quickly and accurately calculate the consequences of different scenarios.

In addition to projecting the effects of an outbreak, such a tool also could be used to evaluate potential mitigation strategies and to guide response. The value of this tool would be expected to increase with the number of users, by providing a common modeling platform with a uniform set of input and result fields. Users would be able to compare assumptions, data inputs, and results. In addition, if the tool were widely used, a future web-based central database of compiled anonymous data could enable the development and use of benchmarks to further aid pandemic planning.

Available Computer Tools for Pandemic Planning

The U.S. Centers for Disease Control and Prevention (CDC) developed, and made available online, a spreadsheet-based computer modeling tool, FluSurge,[1] which estimates the healthcare consequences of an influenza pandemic. The FluSurge user enters population data and the number of available staffed hospital beds (both intensive care unit [ICU] beds and non-ICU beds) and mechanical ventilators, and chooses from one of several attack rates and outbreak durations. FluSurge then applies built-in default assumptions, based on data from the relatively mild pandemics of 1968 and 1957, to calculate week-by-week uti-

Mark N. Abramovich, MBA, is an independent management consultant in New York City. Eric S. Toner, MD, is a Senior Associate and Jason Matheny, MPH, MBA, is a Project Consultant, both at the Center for Biosecurity of the University of Pittsburgh Medical Center, Baltimore, Maryland.

lization rates of hospital beds and ventilators and the number of deaths. FluSurge allowed local planners, for the first time, to easily examine the potential effects of a pandemic on their own communities. However, FluSurge limits hospital planners in several key ways.

First, FluSurge does not reflect the complex and dynamic nature of medical response to a surge event. FluSurge considers only two hospital resources—staffed beds (both ICU and non-ICU) and ventilators—and assumes they have fixed values throughout the epidemic. The model does not consider augmentation (surge) strategies that are likely to be employed to increase capacity. Examples of augmentation strategies include augmenting staffing, increasing the number of beds, discharging patients early, and canceling elective surgeries. Conversely, the number of staff may decrease as healthcare workers become sick, resulting in reduced capacity.

Second, FluSurge cannot be used either to test mitigation strategies or to guide response. For example, in a severe pandemic in which hospital capacity and resources are exceeded, the model does not consider how shortages of needed medical care will affect mortality rates. Further, the model does not consider the potential reduction in mortality that may result from avoiding such shortages.

Third, it is difficult for FluSurge users to adjust the default morbidity and mortality assumptions. These assumptions, which are based on data from the relatively mild 1968 pandemic, generate bed and ventilator utilization rates far lower than those expected in a severe 1918-like pandemic, which may lead planners to underestimate the effects of a severe pandemic. For instance, the pandemic plans for New Jersey[2] and Ontario[3] are based on FluSurge's default settings and anticipate influenza-related mortality rates of less 0.01%—a fraction of the actual average U.S. influenza mortality rate during the 1918 pandemic of 0.66%.[4] (Note that this rate is flu-related mortality rate rather than the more frequently quoted case fatality ratio, which is 2.5%.) In the second version, FluSurge 2.0,[1] some of these assumptions, such as length of stay in the hospital or the percentage of patients requiring mechanical ventilation, can be manually changed by the user from their default values; however, no guidance is provided on alternative values to use to model a more severe pandemic. Such guidance is available in a separate document found at a different website.[5] Some of the built-in assumptions used to calculate the results, such as the age-specific attack and mortality ratios, are completely hidden.

At least one publicly available alternative to FluSurge exists: InfluSim,[6] a model developed at the University of Tübingen in Germany, calculates the daily number of infected individuals, the number of influenza-related work days lost, the number of outpatient visits, the number of hospitalizations, and the antivirals used as well as the attached costs. However, InfluSim does not differentiate between ICU and non-ICU beds, and it does not include the number of ventilators, consider hospital staffing, or allow modeling of response strategies such as canceling elective surgery or early discharge.

A New Model: Panalysis

In this article we describe a new modeling tool, Panalysis (beta version), for use by pandemic planners and medical response managers. The beta version of Panalysis may be accessed at www.panalysismodel.com. Excel was chosen as the platform for the initial version of this tool because it is readily available and familiar to most of the anticipated users. This article is meant to explain our goals and design considerations as well as some of Panalysis' key features. It is not meant to be an instruction manual or an all-inclusive guide to conducting an analysis with the model.

Key features of Panalysis include:

- Many different outbreak scenarios can be quickly modeled, allowing for easy comparison of results; 63 different combinations of epidemiologic curves, attack rates, and severity levels can be chosen without leaving the results screen (see examples online). In addition, multiple pandemic waves can be considered.
- Any size hospital can be modeled. If multiple hospitals in the same community are able to cooperate in a pandemic by sharing resources and patients, then Panalysis can model them collectively as if they were one entity.
- The effects of various surge capacity strategies, such as increasing the number of beds, early discharges, and the cancellation of elective surgeries, can be calculated.
- The effects of increasing the number of personnel or average hours worked can be calculated. Personnel are broken down by categories: physicians, nurses, nurse assistants, respiratory therapists, radiology technicians, and laboratory technicians. Conversely, the effects of staff absenteeism can also be viewed. In addition, the effects of a volunteer program on staff capacity can be calculated.
- The number of available ventilators changes as the epidemic progresses and reserve "surge" ventilators are put into use, including anesthesia machines (mechanical ventilators used in operating rooms to both deliver anesthesia and provide ventilatory support) and recovery-room ventilators freed up by cancellation of surgeries.
- As shortages of beds or ventilators occur, Panalysis will automatically allocate beds and ventilators based on a built-in algorithm. Alternatively, the user can choose to override the algorithm and allocate resources manually.
- Hospital-based outpatient volume is included in addition to inpatient volume.

Overview of Panalysis Goals and Design Considerations

The primary goal of Panalysis is to aid in the effective planning for, and response to, an influenza pandemic that stresses hospital capacity and resources. Model inputs consist of both disease-specific inputs, which define the characteristics of the epidemic in the hospital's community, and hospital-specific inputs, which describe the capacity and resources of the hospital. To aid in the selection of disease-specific inputs, the model includes seven epidemiologic curves from which to choose, some of which are based on historical data.[7]

In addition, ranges of attack rates and severity are provided that are consistent with historical pandemics or government estimates. For hospital-specific inputs, which will vary widely across institutions, default values or ranges are provided in case the user cannot readily provide his or her own data. These default values represent expert opinion or the authors' best judgment. Clearly, the closer these values match the specific characteristics of the user's hospital, the more useful the results will be; therefore, each of these input values can be changed individually if the user is able to obtain more specific data.

An ancillary goal is to provide a framework to guide the underlying planning process. To supply the hospital-specific inputs, the user may be prompted to examine aspects of preparedness or response strategies that have not been considered, such as the number of ventilators and beds that may become available if elective surgeries are cancelled.

Modeling of Patient Surge

Based on the epidemiologic curve, clinical attack rate, and severity chosen by the user, the model calculates the number of new patients for each week of the outbreak. The patients are categorized as requiring initial evaluation (triage), outpatient treatment only, non-ICU hospitalization, or intensive care hospitalization. The logic behind most of the calculations is represented by the flow diagram in Figure 1. Using these results, along with length-of-stay assumptions, the model calculates the weekly hospital census in each category. Based on severity assumptions, the model calculates the number of patients requiring mechanical ventilation and the number of deaths.

The calculation of the number of deaths is complex, since we assume that shortages of ventilators or beds within the hospital would influence the fatality rate. If a patient is in need of mechanical ventilation, but no ventilator is available, the model assumes that the patient will die. If a pa-

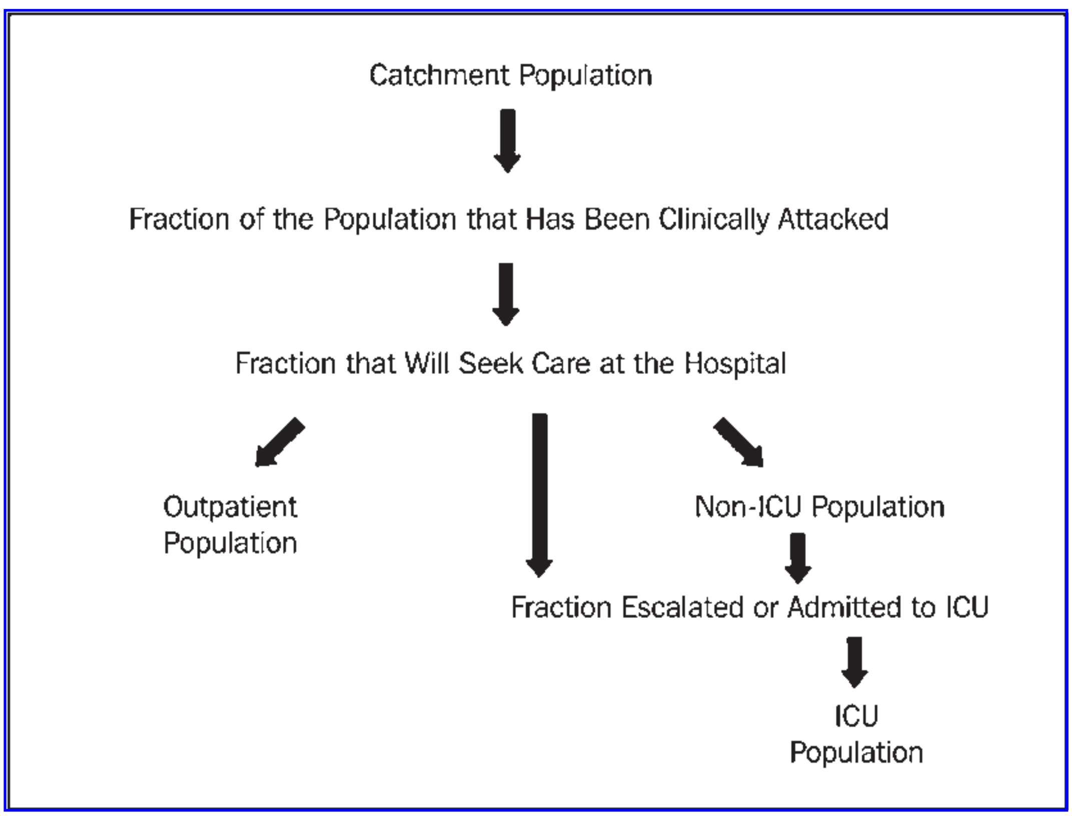

Figure 1. The Flow of Panalysis' Core Data

tient is in need of hospitalization, but no bed is available, the model assigns a fatality rate chosen by the user. Thus, the in-hospital fatality rate is linked to the magnitude of bed and ventilator shortages. And the magnitude of shortages is related to the magnitude of the surge wave, which, in turn, is a function of both the attack rate and the shape of the epidemiologic curve (distribution of casualties). The example in Figure 2 shows how distribution of patients can affect outcome.

Two scenarios with the same number of patients may produce very different magnitudes of shortages depending on the distribution of the patients. Thus, attempts to estimate the consequences of a future pandemic without considering the shape of the surge wave can be misleading. For example, in one scenario using a population of 100,000 and a 330-bed hospital, we applied an epidemiologic curve derived from the second wave of the 1918 pandemic in London. The model projected 461 fatalities, of which 337 occurred in the hospital, in part due to hospital shortages. The second wave of the 1918 pandemic in London had a more gradual curve than the first and third waves. When we held all other variables constant and used the curve from the first wave of the 1918 pandemic—a 7-week curve as opposed to the second wave's 12-week curve—in-hospital and hospital shortage-related deaths increased from 337 to 498, a 48% increase.

For this reason, the model contains a control panel that enables the user to easily model many different scenarios. Through use of such scenario-driven analyses, the user can develop different response strategies for different pandemic scenarios. For example, the user might find that a mild pandemic, like the one in 1968, would not exhaust hospital resources once augmentation strategies are considered. In this case, the focus of pandemic planning for a hospital might be to find the most cost-effective augmentation strategy. On the other hand, a pandemic as severe as the one in 1918 might cause such stress on the hospital's capacity and resources that economic considerations pale in comparison to patient care considerations and the need to avoid catastrophic failure.

Modeling Bed and Ventilator Augmentation

Panalysis allows the user to define up to three phases of bed and equipment augmentation, based on the user's estimates of surge capacity. The model recognizes that while each of the five categories of bed and equipment augmentation (i.e., augmenting manpower, increasing beds, canceling elective surgeries, discharging some patients early, and deploying existing surge ventilators) increases hospital capacity for flu patients, they are not equally useful strategies

Example 1: Population of 10,000, attack rate of 15%, producing 1,500 cases and cases evenly distributed.

WEEK	1	2	3	4	5	6	7	8	9	10
% of cases	10%	10%	10%	10%	10%	10%	10%	10%	10%	10%
Multiplied by 1,500 cases										
# of cases	150	150	150	150	150	150	150	150	150	150

Example 2: Population of 10,000, attack rate of 10%, producing 1,000 casualties with cases not evenly distributed.

WEEK	1	2	3	4	5	6	7	8	9	10
% of cases	1.6%	3.2%	6.5%	12.9%	25.8%	25.8%	12.9%	6.5%	3.2%	1.6%
Multiplied by 1,000 cases										
# of cases	16	32	65	129	258	258	129	65	32	16

In Example 1, there are more total cases, but only 150 cases per week. In Example 2, there are fewer cases overall, but due to the case distribution, weeks 5 and 6 are more severe than any week in Example 1. Assuming that a hospital could handle no more than 200 casualties in any given week, example 2 would cause hospital shortages, but example 1 would not.

Figure 2. The Effect of Different Epidemiologic Curves on the Magnitude of Patient Surge

in all circumstances. For example, canceling elective surgeries or discharging patients early may put patients at risk, and canceling elective surgeries may have negative economic consequences. Hospitals may have different constraints on or preferences about augmentation strategies. Given the many possible permutations, the model provides three decision tools to help the user plan and execute bed and equipment augmentation:

- The Recommended Solution is the default method of calculating bed and ventilator allocation. It is based on an algorithm that calculates a solution given patient-care, operational, and economic constraints.
- The Nonprioritized Solution is an alternative calculation available to advanced users that does not take into account patient-care, operational, or economic constraints.
- The Manual Solution allows the user to override the other two solutions and enter his or her own bed, staff, and equipment figures based on individual considerations.

These three decision tools are described in more detail in Appendix 1.

Modeling Staff Augmentation

Panalysis allows the user to model the effects of augmenting staff by adjusting the number of personnel and their hours worked. In addition, Panalysis can calculate the effects of absenteeism, possible changes in staffing ratios, and the use of volunteers.

- The model arbitrarily assumes that staff members will become sick from the flu at the same rate as the general population and that they will be absent from work for 2 weeks. In addition, the model assumes that for each staff member absent due to illness, one other will be absent to care for sick family members or children home from school.
- In response to high patient volumes, the normal ratio of patient to staff may change as normal patient-care standards and routines are modified. Panalysis allows the user to take this increase in patient:staff ratio into consideration. On the other hand, loss of efficiency due to fatigue, supply shortages, and overtaxed support services may lead to lower than normal patient:staff ratios. The staff capacity multiplier gives the user the option to increase or decrease the number of patients that staff members can handle as a group, depending on the severity of the scenario.
- Possible increases in staff capacity, by personnel category, resulting from the use of volunteers is considered based on user-defined estimates.

Analysis and Planning Using Panalysis

The purpose of the following example is to demonstrate how Panalysis can be used to plan for a severe pandemic. We ran a simulation that would have produced fatalities comparable to those during the second wave of the 1918 influenza in London. We used the actual 12-week curve from this second wave to project our core data onto a catchment population served by a fictitious but typical U.S. hospital.

We assume that the hospital serves a catchment population of 100,000 and has 275 nurses who would normally be available to treat medical inpatients on any given day. We estimate that, by reassigning staff, during peak weeks of the outbreak, the hospital could count on 500 nurses to care for flu patients. In a normal week, we assume that because some nurses work part-time, the average nurse works 25 hours per week, and thus we define 25 hours as one man-week. We estimate that our nursing staff will be able to work on average up to 50 hours per week during the height of the outbreak. We assume that our nurses will become sick at the same rate as the rest of the population and that an infected nurse will be unable to care for patients for 2 weeks. We also assume that for every nurse with the flu, one more nurse will be absent from work to care for sick family members. Based on these assumptions, the model estimates that on week 4, the shortage of nurses will be 154 man-weeks; on week 5, the shortage will be 128 man-weeks. All the data inputs and results from this example can be found in Appendix 2.

Based on this information, mitigation tactics can be created and tested that may yield results that are not intuitively obvious. For example, assuming that some nurses would be willing to work more overtime but are unable to do so because of home childcare issues, an in-home childcare program using pre-screened volunteers might be instituted (the difficulties involved in creating such a program are acknowledged but are beyond the scope of this example). The hospital might find that by facilitating childcare for nurses during the peak weeks, they can increase the average hours worked per nurse from 50 to 53. The result of this modest increase in average hours worked is that on week 4, 53 nurse man-weeks of capacity are gained and nurse shortage drops to 101 nurses from 154, a 34% reduction. For week 5, 50 nurse man-weeks of capacity are gained and the shortage drops to 78 nurse man-weeks from 128, a 39% reduction. This example illustrates how small operational changes can lead to relatively large changes in efficiency for the hospital. In this case, a 6% increase in hours worked reduced shortages during the peak weeks by 34% and 39%, respectively.

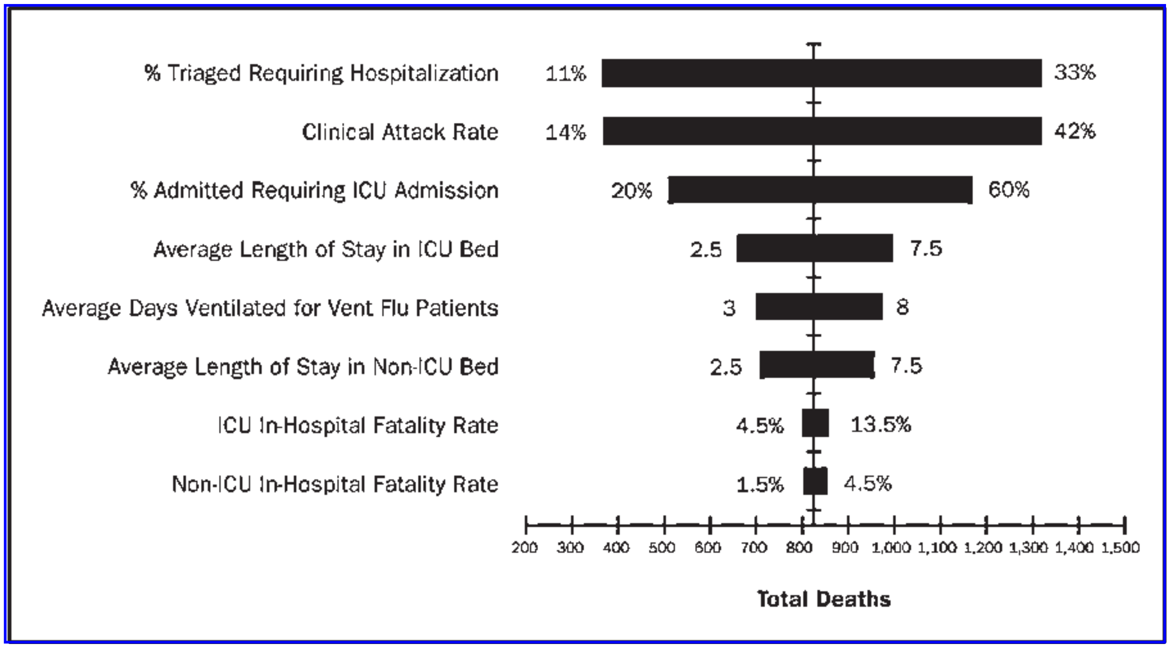

Figure 3. Sensitivity of total deaths to epidemic parameters without using recommended augmentation strategies

Sensitivity Analysis

We undertook sensitivity analyses for parameters that underlie estimates of total flu-related deaths and bed shortages at the peak of a severe pandemic scenario. The analyses included both population-level and hospital-level epidemic parameters, from 50% to 150% of their default values, with or without the use of augmentation strategies. The analyses produced results that were in line with expectations.

Figures 3 and 4 show how the number of total deaths varied with or without use of augmentation strategies. As expected, the number of deaths was sensitive to changes in the clinical attack rate. Because the model links shortages of essential resources to patient outcomes, the number of

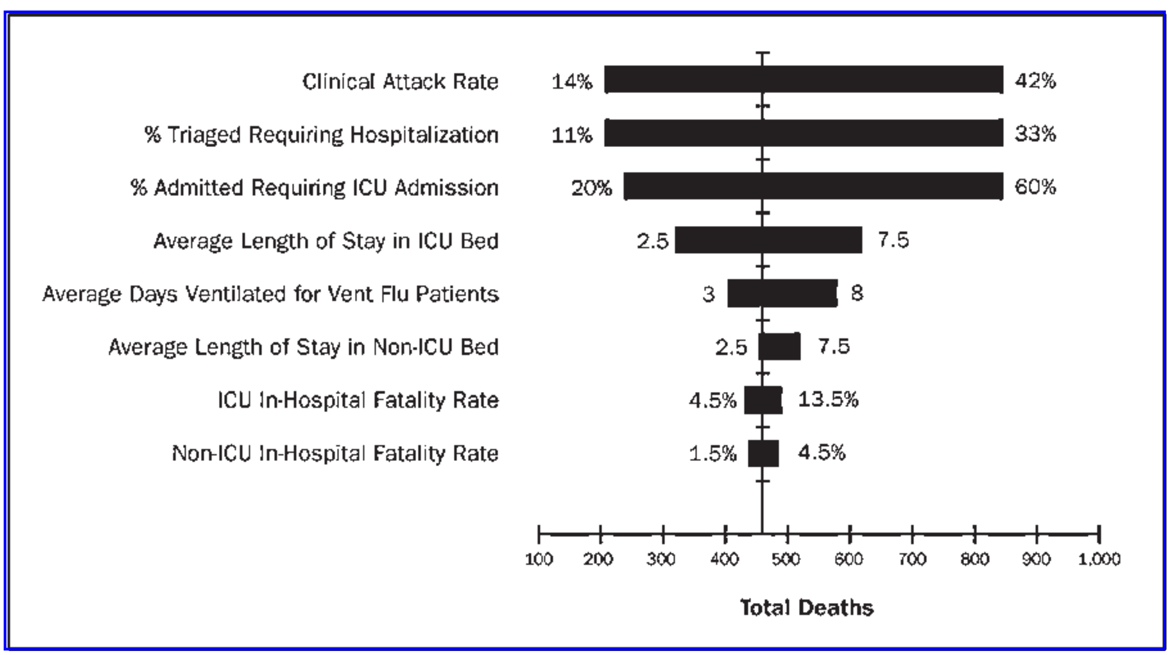

Figure 4. Sensitivity of total deaths to epidemic parameters when using recommended augmentation strategies

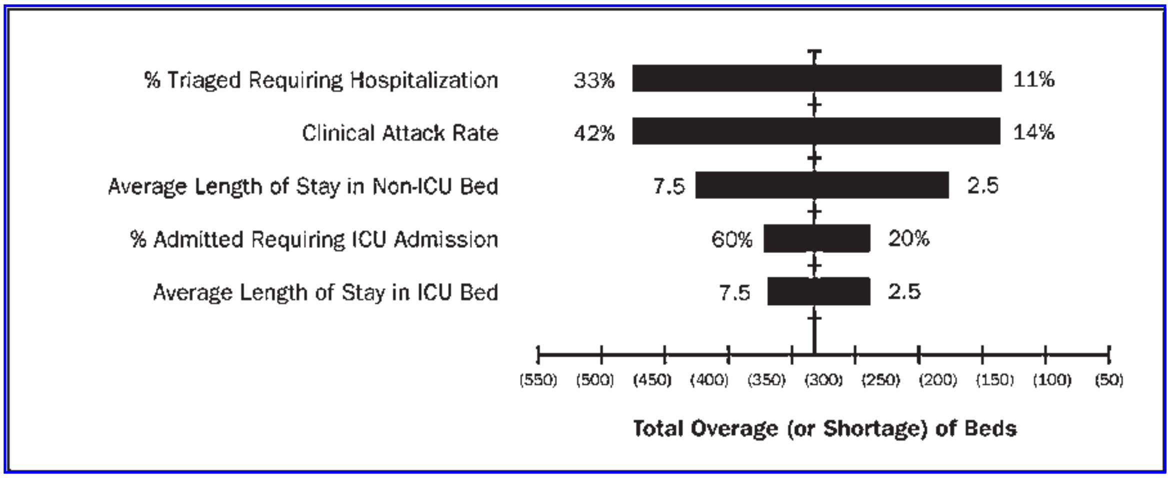

Figure 5. Sensitivity of bed shortages to epidemic parameters without using recommended augmentation strategies

deaths was also sensitive to changes in parameters that relate to hospital resources: required hospitalization percentage, ICU admission percentage, ICU length of stay, and average ventilator days for flu patients. The number of deaths was relatively insensitive to changes of inpatient fatality rate because, in this severe pandemic scenario, the majority of deaths result from shortages of resources. Patients unable to gain access to critical resources (beds and ventilators) because of shortages were assigned fatality rates of 25% for non-ICU bed shortages, 81% for ICU bed shortages, and 100% for ventilators shortages. In contrast, patients not facing shortages were assigned the inpatient fatality rates of 3% for non-ICU patients and 9% for ICU patients. The number of deaths also was relatively insensitive to changes of non-ICU length of stay because of the difference in assigned fatality rate of patients who are unable to have access to a bed: 81% for ICU and 25% for non-ICU. The use of augmentation strategies reduced the impact of the percentage requiring hospitalization on the number of total deaths.

Bed shortage (Figures 5 and 6) was sensitive to the clinical attack rate, the required hospitalization percentage, and the non-ICU length of stay. The effect of ICU-related parameters was low because the number of ICU beds is much lower than the number of non-ICU beds. Using recommended augmentation strategies decreased bed shortages by between 118 and 184 beds.

Future Development

Panalysis is currently undergoing beta testing and refinement. In addition, a number of improvements and additional features are in various stages of development. We have chosen to make the beta version of Panalysis available at this time to encourage comment and feedback from the pandemic preparedness community. Some of the additional features in development include a user-customizable supply module that includes supply costs and a staff sched-

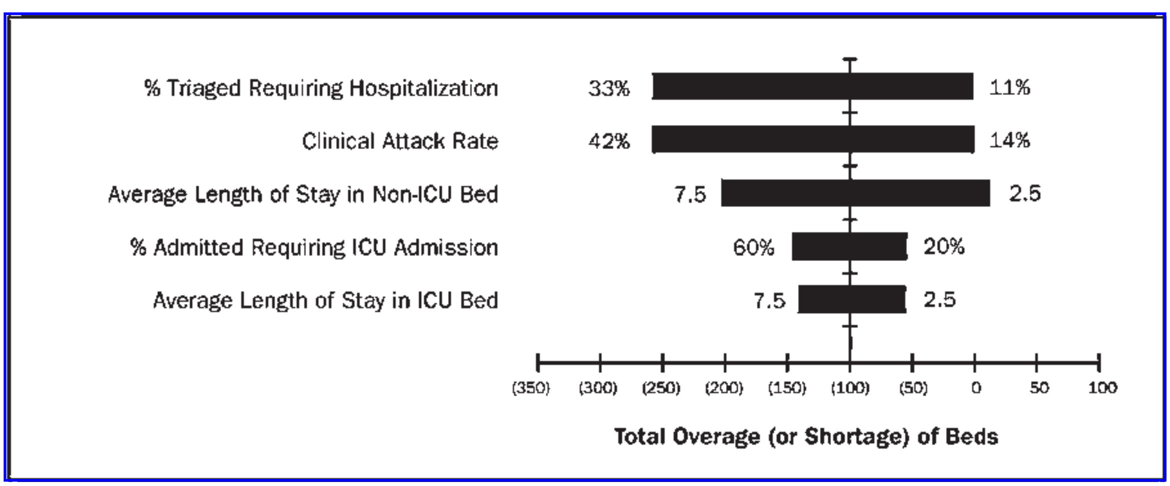

Figure 6. Sensitivity of bed shortages to epidemic parameters when using recommended augmentation strategies

uling module that includes staffing costs and estimates overtime costs.

A web-based version of Panalysis could allow anonymous data to be collected for benchmarking and model refinement. Individual hospitals could quantify their level of preparedness and compare their results to those of other hospitals and regions. Compiled data would improve the default values used in the model. For example, several different profiles (e.g., large teaching hospital, mid-size community hospital, small rural hospital) could be created from the database with different default input values.

Conclusion

Existing pandemic planning models for health care enable the user to calculate some potential shortages through the distribution of casualties using historical data. Panalysis improves on these tools by including the dynamic relationship between patient surge and limited resources and by enabling the testing of mitigation and response strategies.

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Address reprint requests to:
Mark N. Abramovich
43 East 10th Street, Apt. 5-H
New York, NY 10003

E-mail: m.abramovich@att.net

Appendix 1. Three Methods of Calculating Bed and Ventilator Augmentation

The Recommended Solution

The Recommended Solution is the default method of calculating bed and ventilator allocation. It is based on an algorithm that automatically calculates a solution given patient-care, operational, and economic constraints. The algorithm identifies three possible bed and/or ventilator shortage scenarios for both ICU and non-ICU areas (see Figure A1).

Scenario I

There is a shortage of beds but not of ventilators. In this case, the model exhausts bed augmentation possibilities before it cancels elective surgeries or discharges patients early. If it cannot satisfy the shortage by adding additional beds, it selects the minimum number of early discharges, cancels the minimum number of elective surgeries, or combines both strategies as needed. If this solution fails, it cancels all elective surgeries and discharges early the maximum number of patients allowed.

Scenario II

There is a shortage of ventilators but not of beds. If deployment of unused and then surge ventilators does not relieve the shortage, elective surgeries are canceled to free additional ventilators. This algorithm does not consider bed or early discharge strategies, as these strategies have no bearing on hospital ventilator capacity. The model also allocates surge ventilators first to ICU and then to non-ICU beds. It also cancels non-ICU surgeries to free ventilators for the ICU and vice versa if one area, but not the other, is short.

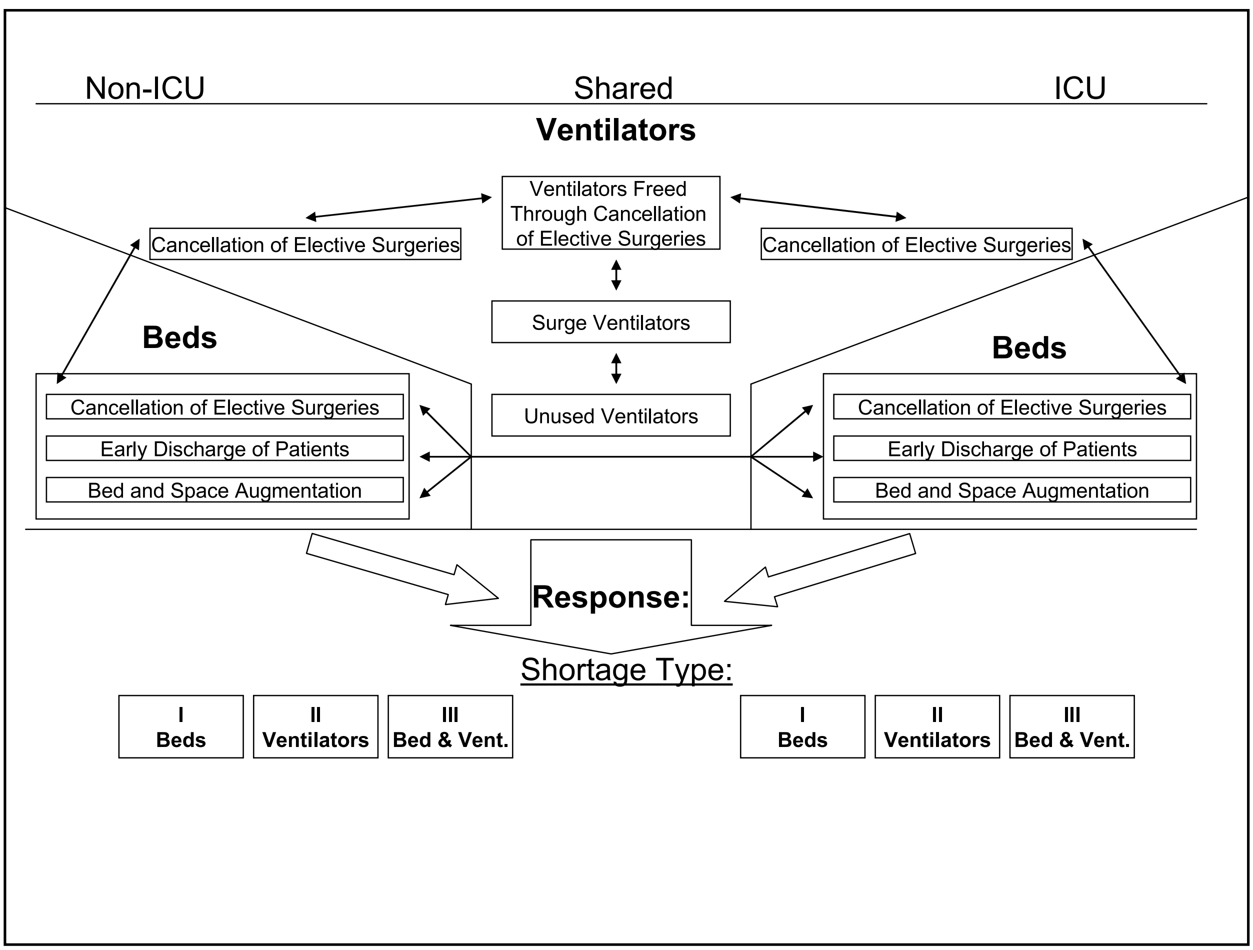

Figure A1. Graphic Representation of the Recommended Solution

Scenario III

There is a shortage of both ventilators and beds. Here the model first cancels elective surgeries, freeing both ventilators and beds. It does this until the ventilator shortage has been eliminated. If canceling elective surgeries does not provide sufficient bed augmentation, it then exhausts its bed strategies as well as its early discharge strategies.

For either of the two scenarios that take into account ventilator shortages (II and III), we consider that hospitals have a finite number of full-function ventilators that are normally used. In addition, many hospitals have a small cache of older-model or backup ventilators as well as limited-function transport ventilators. Some hospitals have purchased and stockpile emergency ventilators for use in a disaster. We categorize all of these additional ventilators as "surge ventilators." Additionally, as elective surgeries are canceled, a certain number of additional ventilators become available, including both recovery room and ICU ventilators. The model also assumes that anesthesia machines can be used as ventilators if surgeries are canceled. Here, the model first exhausts the normal stock of unused ventilators, and then any additional surge ventilators are distributed as needed.

For both beds and ventilators, the algorithm cross-allocates resources in the event that either the non-ICU or ICU has a shortage while the other has an overage.

The Nonprioritized Solution

The Nonprioritized Solution is an alternative calculation method that replaces resources one by one where there is a shortage, until any single resource has been exhausted. However, it does not take into account patient-care, operational, or economic constraints. It considers only the maximum number of any resource available. For example, in the event of a ventilator shortage, ventilators are added until all normal ventilators, surge ventilators, and ventilators that could potentially be freed from canceling elective surgeries have been allocated. However, this method of calculation does not cancel any of the requisite surgeries. This approach allows the user to precisely pinpoint allocation requirements for non-ICU beds, ICU beds, and ventilators, but it does not address any of the constraints previously discussed.

The Manual Solution

The Manual Solution allows the user to override the other two solutions and enter his or her own bed and ventilator figures.

Appendix 2. Example of Data Inputs and Results

Hospital-specific Inputs (baseline)

Catchment Population	
Total Catchment Population	100,000

Non-ICU Bed Capacity	
Non-ICU bed capacity per hospital	300
Average % occupancy	85%
Average length of stay (days)	4
Average inpatient mortality rate	1%

ICU Bed Capacity	
ICU bed capacity per hospital	30
Average % occupancy	70%
Average length of stay (days)	3
Average inpatient mortality rate	10%

Elective Surgeries	
Average number of non-ICU beds used per day for elective surgeries	30
Average number of ICU beds used per day for elective surgeries	5
Average number of elective surgeries per day (outpatient)	90
% elective surgeries that use an anesthesia machine	80%
Average surgeries per anesthesia machine per day	5
% elective surgeries that use a recovery room ventilator	10%
% elective surgeries that require an ICU ventilator	90%
Average surgeries per recovery room ventilator per day	4
Average number of elective surgeries that use an ICU ventilator per day	4
Average duration (days) of ventilator use (for elective surgery patients needing ICU ventilator)	1

Triage Assessment Capacity	
Emergency department capacity (per day)	200
Clinic capacity (per day)	100
% Utilization[a]	80%

[a]The model has a built-in method for utilization rate calibration.

Staff (personnel that would normally be involved in the care of medical patients)	
Number of doctors available per hospital	150
Average hours per week	15
Number of nurses available per hospital	275
Average hours per week	25
Number of nurse assistants available per hospital	200
Average hours per week	25
Number of respiratory therapists available per hospital	20

Average hours per week	25
Number of radiology techs available per hospital	30
Average hours per week	25
Number of lab techs available per hospital	30
Average hours per week	25

Respiratory Equipment	
Number of ventilators available	32
% non-ICU bed patients requiring ventilator per day	1%
% ICU bed patients requiring ventilator per day	50%
Average number of days ventilated for non-ICU patients requiring ventilation	3
Average number of days ventilated for ICU patients requiring ventilation	5
Number of other surge ventilators (old ventilators, transport ventilators, etc.)	8

Hospital Augmentation Capacity Inputs

Staff Augmentation

Number of doctors available during crisis	200
Average hours worked per week during crisis	30
Number of nurses available during crisis	500
Average hours worked per week during crisis	50
Number of nurse assistants available during crisis	400
Average hours worked per week during crisis	50
Number of respiratory techs available during crisis	22
Average hours worked per week during crisis	50
Number of radiology techs available during crisis	32
Average hours worked per week during crisis	50
Number of lab techs available during crisis	32
Average hours worked per week during crisis	50
Staff capacity multiplier (to increase or decrease patient:staff ratios depending on the severity of the outbreak)	10%

Bed, Ventilator, and Triage Augmentation

Planned Response by Phase	**Phase 1**	**Phase 2**	**Phase 3**
Bed Augmentation			
Gain in beds (non-ICU)	10%	20%	30%
Gain in beds (ICU)	10%	20%	30%

Early Discharges[b]			
Gain in beds (non-ICU)	5%	10%	15%
Gain in beds (ICU)	5%	10%	15%
Cancellation of Elective Surgeries[b]			
% elective non-ICU surgeries canceled	33%	66%	100%
% elective ICU surgeries canceled	33%	66%	100%
Percent by which triage volume can be increased during a crisis[c]			100%

[b]The effects of discharging patients early and canceling elective surgeries is "normed" in terms of beds created. In actuality, these strategies free beds rather than create them.

[c]Triage shortages are not calculated by phased response; additional capacity is added as needed.

Volunteer Augmentation

Will volunteers be used to augment hospital staff? (answer yes or no)	No
Increase in capacity doctors	5%
Increase in capacity nurses	10%
Increase in capacity nurse assistants	30%
Increase in capacity respiratory techs	5%
Increase in capacity radiology techs	5%
Increase in capacity lab techs	5%

Disease Specific Inputs

Epidemiologic Curve

Week 0	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6	Week 7	Week 8	Week 9	Week 10	Week 11	Week 12
0%	1%	4%	13%	22%	20%	13%	10%	8%	5%	2%	1%	1%

Clinical attack rate	28%
Relative Age Distribution of Illness	
Age 0–18	29.9%
Age 19–64	63.9%
Age 65+	6.1%
% sick seeking hospital care (triaged)	25%
% triaged requiring hospitalization	22%
Average length of stay in non-ICU bed (days) (range from 1–14)	5
% admitted requiring ICU	40%
Average length of stay in ICU bed (days) (range from 1–14)	5

Distribution of Hospitalizations by Age Range (Non-ICU and ICU)	
Age 0–18	22%
Age 19–64	47%
Age 65+	31%
% of ICU flu patients requiring ventilation	75%
Average days ventilated for flu patients requiring ventilation	5
Number of pandemic waves	3
Distribution of Deaths by Age	
Age 0–18	22%
Age 19–64	47%
Age 65+	31%
Flu Fatality Rates	
Non-ICU (assuming no bed or ventilator shortage)	3.00%
ICU (assuming no bed or ventilator shortage)	9.00%
Fatality rate if unable to access needed non-ICU bed	25.00%
Overall fatality rate: nonhospitalized population	0.124%

Hospital Capacity Results Before Pandemic and on a Peak Week

	Week 0	**Week 4**
Total number of catchment population sick with flu	0	6,153
Average number of non-ICU beds normally occupied per day	255	255
Average number of non-ICU beds occupied per day by flu patients	0	242
Average number of non-ICU beds occupied per day	255	497
Average number of non-ICU admissions per week	446	785
Average number of non-ICU admissions per week due to flu	0	338
Average number of non-ICU discharges per week	446	785
Augmented bed capacity (including early discharge and cancel electives)	300	465
Overage (or shortage) of non-ICU beds (with augmentation)	45	(32)
% occupancy non-ICU beds (with augmentation)	85%	111%
Overage (or shortage) of non-ICU beds (without augmentation)	45	(197)
% occupancy non-ICU beds (without augmentation)	85%	166%
Average number of ICU beds occupied per day normally without augmentation	21	21
Average number of ICU beds occupied per day by flu patients	0	97
Average number of ICU beds occupied per day	21	118
Average number of ICU admissions	49	184

Average number of ICU admissions due to flu	0	135
Average number of ICU discharges	49	184
Augmented ICU capacity (including early discharge and cancel electives)	30	49
Overage (or shortage) of ICU beds (with augmentation)	9	(69)
% occupancy ICU beds (with augmentation)	70%	243%
(Shortage or) overage of ICU beds without augmentation	9	(88)
% occupancy ICU beds without augmentation	70%	392%
Total overage (or shortage) of beds (ICU and non-ICU)	54	(101)
Total elective surgeries canceled	0	125
Outpatient visits	1,680	3,218
Additional outpatient assessments due to flu	0	1,538
Triage shortage	0	(698)
Flu patients sent home after outpatient assessment	0	1,200

Ventilator and Fatality Results Before Pandemic and on a Peak Week

Ventilator Overage and Shortages	Week 0	Week 4
Ventilators needed for flu patients only	0	73
Ventilators needed per day	19	92
% ventilator utilization without surge ventilators	61%	287%
Ventilator shortage without surge ventilators (overages will not appear)	0	(60)
Surge ventilators deployed	0	8
Ventilator shortage without canceling surgeries	0	(52)
Ventilator gain from cancellation of elective surgeries	0	23
Ventilator overage (or shortage)	13	(29)
Ventilator utilization with surge ventilators	61%	146%

Deaths	Week 0	Week 4
Deaths among nonhospitalized flu victims	0	27
Deaths occurring in hospital or due to hospital shortages[d]	0	115
Total deaths	0	142

[d]Deaths as the result of bed shortages are accounted for here; therefore, "deaths in-hospital" can exceed hospital admissions.

Summary Statistics

Total flu cases	28,000
Total flu cases requiring non-ICU beds	1,540
Total flu cases requiring ICU beds	616
Total outpatients	5,460
Total patients triaged	7,000
Total non-ICU bed days used by flu patients	7,700
Total ICU bed days used by flu patients	3,080
Total deaths from flu	461
Total deaths occurring in hospital	337
% of deaths occurring in hospital	73%

Case Fatality Ratios (age specific)			
Overall	0–18	19–64	65+
1.65%	1.21%	1.21%	8.47%