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Major Article

Hospital influenza pandemic stockpiling needs: A computer simulation

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Background: A severe influenza pandemic could overwhelm hospitals but planning guidance that accounts for the dynamic interrelationships between planning elements is lacking. We developed a methodology to calculate pandemic supply needs based on operational considerations in hospitals and then tested the methodology at Mayo Clinic in Rochester, MN.
Methods: We upgraded a previously designed computer modeling tool and input carefully researched resource data from the hospital to run 10,000 Monte Carlo simulations using various combinations of variables to determine resource needs across a spectrum of scenarios.
Results: Of 10,000 iterations, 1,315 fell within the parameters defined by our simulation design and logical constraints. From these valid iterations, we projected supply requirements by percentile for key supplies, pharmaceuticals, and personal protective equipment requirements needed in a severe pandemic.
Discussion: We projected supplies needs for a range of scenarios that use up to 100% of Mayo Clinic–Rochester's surge capacity of beds and ventilators. The results indicate that there are diminishing patient care benefits for stockpiling on the high side of the range, but that having some stockpile of critical resources, even if it is relatively modest, is most important.
Conclusions: We were able to display the probabilities of needing various supply levels across a spectrum of scenarios. The tool could be used to model many other hospital preparedness issues, but validation in other settings is needed.

Of the 4 influenza pandemics during the past 100 years (1918, 1957, 1968, and 2009), only the 1918 influenza pandemic is considered severe in terms of morbidity and mortality. It was responsible for 50-100 million deaths worldwide.[1] Approximately one-third of the American population was infected, with a case fatality rate (CFR) of approximately 2.5%.[1] Such a pandemic today would no doubt overwhelm hospitals.[2] Hospital pandemic preparedness has been hampered by a lack of sufficiently specific planning guidance.[3] In large part, this is because differences among hospitals and between various pandemic scenarios make it difficult to provide useful guidance that is broadly applicable to all hospitals.

The US Department of Health and Human Services released its initial hospital pandemic guidance in 2006.[2] Although this guidance covered many important areas of hospital preparedness, there were significant gaps and generalities, such as advice to "stockpile enough supplies and medications" and "consider ways to increase surge capacity." How hospitals should best do this remains unclear.

The elements for consideration in hospital pandemic planning and health care surge capacity have been well described,[2,4] but the complex and dynamic interrelationships between these elements must be taken into consideration. For this reason several computer-based decision-making tools have been developed.[3,5-7]

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Conflicts of interest: MNA is principal, Interdisciplinary Solutions, LLC, New York, NY, which owns the rights to Panálysis. EST, AAA, and JCH were consultants to Interdisciplinary Solutions, LLC.

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Although useful, these tools were limited particularly with respect to dealing with the many uncertainties inherent in hospital pandemic planning and the operational interdependencies of response activities. For example, changing bed or ventilator capacity affects staffing, supply, and pharmaceutical needs and vice versa. Previous models also did not adequately account for operational chokepoints and bottlenecks, such as emergency department throughput and dynamic staffing patterns.

This report describes a detailed and nuanced computer-aided modeling tool that can enable rational resource-related decision making for hospital pandemic preparedness. The specific goals of this project were to develop a methodology to calculate influenza pandemic supply stockpile needs based on variable operational considerations in individual hospitals and then to test the methodology at Mayo Clinic Hospital–Rochester (Mayo Clinic), a major regional referral medical center with a large local population catchment area.

Previous research has provided pockets of information related to stockpiling, primarily pharmaceuticals, for pandemics.[8-13] Although cost is a factor in making stockpiling decisions, costs analysis was not included in our analysis. Additional analyses will be needed to determine the economic feasibility of preparing for a specified level of influenza pandemic scenarios based an organization's risk tolerance.

METHODS

A modified version of a previously described computer modeling tool, Panálysis (Interdisciplinary Solutions, LLC, New York, NY), was used for this study.[4] Inputs to the model were determined in several ways.

The range of likely epidemiologic variables (eg, clinical attack rate, hospitalization rate, hospital length of stay by unit type, percent requiring mechanical ventilation, and case fatality rate) for a local US portion of a severe influenza pandemic was determined by review of the literature and/or expert consensus of the project team (Table 1). The shape of the epidemiologic curve was taken from the second wave of the 1918 influenza pandemic in London, England.[17] It was selected because it is the most relevant historical example we could find and it is consistent with epidemiologic curves used in other influenza pandemic modeling efforts.

Table 1
Ranges of disease profile variables used in the simulation

Disease profile characteristics	Low end of range	High end of range	Range in literature	Reference
Clinical attack rate	22	38	30	7
			30	14
			30	8
Infected seeking care at hospital (triaged)	5	55	39	15
Triaged requiring hospitalization on a non-ICU unit	15	40	85	7
Average time spent in a non-ICU bed (d)	3	12	5	8
			11	15
Admitted to the hospital that require ICU admission	20	50	25	14
			15	8
			26	15
Average time spent in an ICU bed (d)	4	14	10	8
			10	15
ICU patients requiring mechanical ventilation	30	80	60	14
			50	8
Average time ventilated (d)	3	12	10	8
Non-ICU fatality rate assuming no shortages	3	6	N/A	—
ICU fatality rate assuming no shortages	10	60	N/A	—
CFR for the nonhospitalized population	0	0.3	0.11	16

NOTE. Values are presented as % unless otherwise noted.
CFR, case fatality rate; *ICU*, intensive care unit; *N/A*, not available.

Mayo Clinic provided catchment population data. We assumed Mayo Clinic would provide care for its entire geographic catchment population. Age distribution was determined through US census data.

CFR was used as a proxy of severity. So that the effect of various shortages could be explored, we used 3 different CFRs, which together comprised the population-based rate:

- The CFR of patients who died outside the hospital,
- The CFR in a nonintensive care unit (ICU) bed, and
- The CFR for ICU patients and for patients on a ventilator.

These CFR values were determined by expert opinion of the investigators and normalized to collectively equal the expected population-based CFR of 0.93% ± 0.23%. To determine this value, we estimated that if an influenza pandemic of the same severity as occurred in 1918 occurred today the CFR would be reduced from the historic 2.5% to 0.93% due to advances in medical technology. See supplemental information for more details. This value falls within the midrange of those used by other researchers for modeling a severe pandemic (0.25%-2.1%).[8,16] We used a ±25% tolerance range of 0.93% ± 0.23% to account for uncertainty.

Key pharmaceuticals and supplies needed for hospitalized influenza patients, including those patients requiring critical care services and mechanical ventilation, were determined by expert opinion of the investigators. We only included supplies without which there would likely be a significant degradation in patient outcome and which could not be shared. Our list of essential pharmaceuticals and supplies is available in online supplemental information.

We surveyed Mayo Clinic to determine the total number of existing beds, potential surge beds, physicians, nurses, and patient care assistants that could be available by nursing unit and then estimated the occupancy of these beds by noninfluenza patients during a pandemic for each nursing unit. Out-of-state patients were excluded from our calculation under the assumption that in the context of a severe pandemic travel from out of state would be significantly reduced for elective hospital admissions because of public fear, travel warnings, or Mayo Clinic's operational decisions to postpone elective admissions.[18,19] From this, we projected the number of available influenza beds and categorized available beds by whether they could support a ventilated patient or not.

To project the number of ventilators and anesthesia machines that could be available at Mayo Clinic during an influenza pandemic, we counted the total number of ventilators and anesthesia machines in the hospital and determined their normal use rates. We then adjusted the use rates to account for the cancelation of elective surgeries and for absence of out-of-state patients to determine the number that could be available during a pandemic. We also took into account the number of respiratory therapists at Mayo Clinic and the number of patients they could care for to assess whether personnel or machines were the limiting factor. Nursing staffing was also modeled and will be reported elsewhere.

These data and assumptions were incorporated into a version of Panálysis[4] that was modified to incorporate Monte Carlo simulation, enabling thousands of scenarios each with slightly different assumptions to be modeled. Panálysis runs on Excel (Microsoft Corp, Redmond, WA) and the Monte Carlo simulations were performed with @Risk version 6 for Excel (Palisade Corp, Ithaca, NY).

Various response options were analyzed in the iterative model runs. Constraints were applied to the model to exclude iterations which violate logic or predefined parameters. For example:

- The fatality rate for critical care patients must be greater than or equal to the fatality rate for patients assigned to medical/surgical wards due to greater severity of illness.
- The population-based CFR must be between 0.70% and 1.16% (0.93% ± 25%) (see above).
- Total fatalities within the Mayo Clinic geographic catchment population must be between 305 and 508. We reduced the historic 1918 US influenza mortality rate in of 0.66% in proportion to the reduction of the CFR from 1918 to the present, as discussed above. This ratio was then multiplied by the catchment population of Mayo Clinic and again we used a ±25% tolerance range to account for uncertainty.
- There must not be an absolute shortage of beds or ventilators (taking into account surge resources). The goal was to estimate the amount of supplies expended if every possible bed and ventilator was used. If there is no bed or ventilator, no supplies are needed.
- The time spent on a ventilator must be between 50% and 90% of the time spent in an ICU bed.

To test Mayo Clinic's bed and ventilator capacity during an influenza pandemic we also ran scenarios in which beds were constrained but not ventilators and vice versa. Based on these results, we determined the percent of scenarios in which Mayo Clinic would have sufficient beds but not ventilators, ventilators but not beds, and a sufficient number of both.

Our model simulates a surge in hospital patient volume based on epidemiologic parameters and detailed hospital capacity data collected from Mayo Clinic (listed above). The model projects inpatient census week by week during a pandemic by nursing unit type, accounting for varying lengths of stay, movement between unit types, and in-hospital deaths. Weekly resource needs are tallied, including beds, staffing, ventilators, key pharmaceuticals, and supplies. The model's logic assumes that if a patient is in need of mechanical ventilation, but no ventilator is available, the patient would die. If a patient 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 patient surge wave, which, in turn, is a function of both the attack rate and the shape of the epidemiologic curve.

Throughout the model development, we validated equations and parameters against their sources, maintained careful documentation of the code, walked through the model with other experts to search for errors, and performed sensitivity analyses. The sensitivity analyses were particularly useful because, as is typical in such projects, odd results become powerful aids for model verification. Such results emanate from 1 of 3 things. First, they can reveal a hidden assumption that needs to be relaxed or sharpened. Second, they occasionally identify an error in the programming that needs to be fixed. Third, they sometimes suggest a nonintuitive relationship that, upon further study, turns out to be perfectly reasonable.

The spectrum of model outputs were presented to Mayo Clinic administrators for their consideration of the hospital's stockpiling needs.

RESULTS

The resultant graphs and statistics were based on 10,000 iterations of a simulation using different combinations of variables. Each iteration corresponds to a specifically generated influenza pandemic scenario. Of these, 1,315 scenarios fell within the parameters defined by our simulation design and constraints and 8,685 were disqualified. From the 1,315 valid influenza pandemic scenarios, we projected supply requirements by percentile for a variety of medical supplies, pharmaceuticals, and personal protective equipment items. From the results, planners could select a supply level for each product that would be sufficient for a percentile of pandemic scenarios. For discussion and planning purposes, a supply level that was sufficient for 95% of pandemic scenarios was emphasized. Supply levels derived from the model could be coordinated with identified limiting factors to allow for efficient planning.

As an example, Figure 1 displays the model output for 4 key resources: oseltamivir, ventilator circuits, N95 respirators (following state use guidelines), and gloves. These cumulative probability graphs show the number of units of each resource (for oseltamivir it shows the number of treatment courses) that are needed across the distribution of included scenario iterations. For example, the graph shows that 4,998 courses of oseltamivir would be sufficient for 95% of scenarios and approximately 4,000 courses would be sufficient for 88% of scenarios. One can see that relatively little incremental benefit is gained by the additional 1,000 courses. On the other hand, only 2,200 courses are needed for half the scenarios.

To help illustrate the range of possible scenarios and to put the individual supply results in context, we constructed 9 base case scenarios each intended to highlight some particular aspect of the disease profile characteristics (Table 2) and the resulting supply implications of a few representative items (Table 3).

DISCUSSION

No severe influenza pandemic has occurred in the age of modern medicine and it is unclear how well the characteristics of mild-moderate influenza pandemics or seasonal influenza can be applied to a severe influenza pandemic. The resulting uncertainty complicates the task of pandemic planning.

Even if one could predict the epidemiologic characteristics of a new severe influenza pandemic, there still would be great uncertainty as to the number of hospitalizations that would occur given the dramatic changes in medical care during the past century. Modern medical care, if available, can reduce the number of severe cases and deaths but because so much more is done for inpatients, hospitals are more vulnerable to being overwhelmed.

Severity of pandemics is defined primarily by mortality rates. However, because mortality rates are a function of the number of people infected, the severity of the illness, and the resources available to treat the patients, different pandemic scenarios with the same mortality rates can have very different influence on hospitals. For example, an influenza pandemic that is very intense but brief would have a greater influence than an influenza pandemic that produces the same number of severe illnesses over a longer time frame. Additionally, a large referral hospital such as Mayo Clinic that has a comparatively large capacity relative to the size of its catchment population could be expected to have fewer shortages than other hospitals, resulting in fewer inpatient deaths.

Hospitals often use a single scenario when developing a pandemic plan. Such optimization approaches seek to find what's best out of a number of possible decisions, based on well-defined inputs. However, in light of the many uncertainties inherent in a pandemic, a single scenario is inadequate for the development of stockpile plans. Therefore, we used Monte Carlo simulation to generate a multitude of what-if scenarios randomly across the spectrum of reasonable variables and then displayed and analyzed the results to understand the frequency and range of possible outcomes. A Monte Carlo model calculates potential outcomes by first substituting probability distributions for uncertain input factors and then samples results over and over, possibly thousands of times. Although Monte Carlo simulation cannot not identify the single best strategy, it allows the decision maker to understand the range of

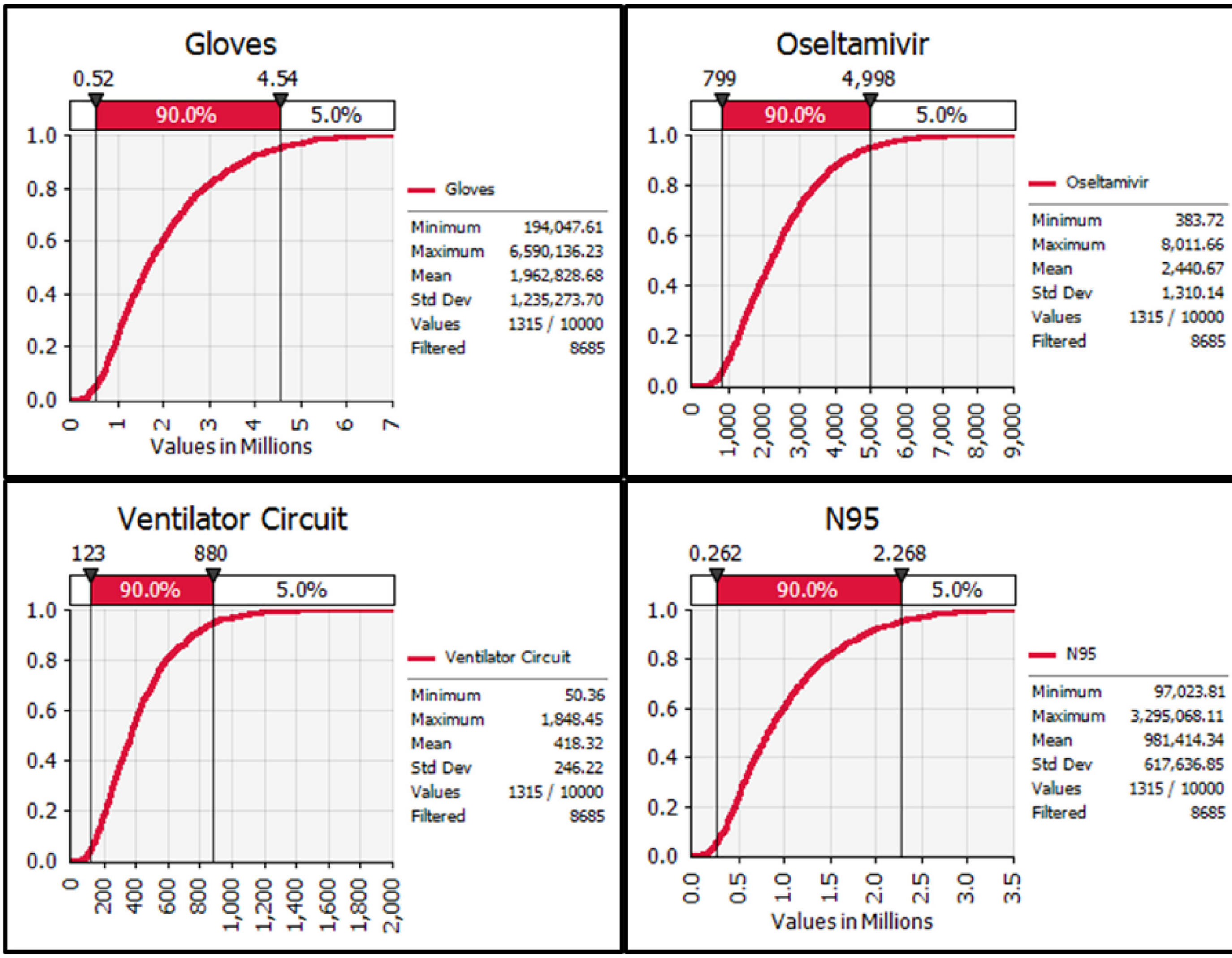

Fig 1. Examples of the numbers of various resources needed by percentile of scenario iterations.

Table 2
Disease profile characteristics for the 9 base cases (BCs)

	BC								
Disease profile characteristics, fatalities, and fatality rates	1	2	3	4	5	6	7	8	9
Attack rate									
Clinical attack rate	35	30	26	30	32	32	32	38	30
Hospitalizations									
Attacked seeking hospital care (triaged in emergency department)	20	5	35	30	20	24	15	20	8
Triaged requiring hospitalization	22	15	18	20	32	20	23	22	15
Average length of stay in a noncritical care bed (d)	5	5	5	10	10	10	7	5	12
Admitted that require critical care	40	50	30	40	40	40	40	25	50
Average length of stay in a critical care bed (d)	7	7	5	10	13	13	10	7	14
Ventilation									
Critical care patients requiring ventilation	60	60	50	80	60	60	70	60	60
Average ventilation time for pan flu patients (d)	5	5	4	9	8	8	9	5	13
Fatalities									
Noncritical care fatality rate assuming no shortage	3.5	3.0	4.0	3.5	4.2	3.0	5.0	3.0	6.0
Critical care fatality rate assuming no shortages	22	60	22	21	25	16	50	15	60
Fatality rate of nonhospitalized population	0.135	2.000	0.100	0.068	0.000	0.150	0.230	0.225	0.200
Total fatalities (n)	467	395	394	407	419	424	431	495	475
Clinical fatality rate	0.93	0.91	1.05	0.94	0.93	0.92	0.93	0.86	1.10

NOTE. Values are presented as % unless otherwise noted. Each base case includes a different mix of assumptions designed to illustrate a range of outcomes.

Table 3
Calculated supply results for the 9 base cases (BCs)

Supplies—totals needed	BC 1	BC 2	BC 3	BC 4	BC 5	BC 6	BC 7	BC 8	BC 9
Oxygen delivery mechanism									
Adult nasal cannula or oxygen mask	2,332	365	2,304	2,532	3,102	2,326	1,672	2,261	584
Child nasal cannula or oxygen mask	777	122	768	844	1034	775	557	754	195
Pulse oxymitery probes	1,777	325	1,418	1,558	2,363	1,773	1,274	1,206	519
BiPap mask	444	81	354	389	591	443	318	301	130
IV infusion sets									
Catheter (for IV set)	9,266	1,530	8,695	9,711	12,089	9,067	6,880	8,097	2,559
Tubing (for IV set)	9,266	1,530	8,695	9,711	12,089	9,067	6,880	8,097	2,559
Lock (for IV set)	9,266	1,530	8,695	9,711	12,089	9,067	6,880	8,097	2,559
IV solution	20,715	3,225	19,345	58,596	72,323	54,242	23,674	20,274	17,139
Foley catheter	635	116	567	701	727	545	573	431	241
Soft wrist retraints	635	116	567	701	727	545	573	431	241
IV infusion pumps with tubing	1,269	232	1,134	1,402	1,454	1,091	1,147	861	482
Central line set	635	116	567	701	727	545	573	431	241
Arterial line set	635	116	567	701	727	545	573	431	241
Endotracheal tube holder	635	116	567	701	727	545	573	431	241
Orgogastric tube	635	116	567	701	727	545	573	431	241
Suction canisters	635	116	567	701	727	545	573	431	241
Yankauer suction catheter	635	116	567	701	727	545	573	431	241
Endo tracheal tube	635	116	567	701	727	545	573	431	241
Ventilator circuit	635	116	567	701	727	545	573	431	241

NOTE. This graph shows projected supply needs for each BC shown in Table 2. Values are presented as number.
IV, intravenous.

potential outcomes and how they change based on differing assumptions.

Rather than focus on the likelihood of a single historical scenario, we focused on justifiable end points for the numerical ranges of our assumptions. We selected broad ranges that we could justify based on historical precedent or expert judgment. Within these ranges, we could not identify a rational basis for assigning a particular probability to any value; therefore, a uniform distribution was used to assign an equal probability to each value in a given range per iteration of the simulation. Not all combinations of variables make sense. For example, it is illogical to have a patient spend more time on a ventilator than in a bed. Therefore, constraints were applied to narrow the range of combinations of variables that were allowable.

The validity of the model output depends on the quality of the data input. Some of the data values are straightforward; for example, the number of beds or ventilators; but much of these data require substantial research and judgment, such as how many elective surgeries can be canceled, or the number of staff members who may be unable or unwilling to report to work. As such, the model's results are specific to the hospital from which the input values are derived and cannot be generalized to dissimilar hospitals. Considerable time is required to collect these data and it requires the involvement of personnel from many departments. Ensuring that the data and assumptions that inform the model are as accurate as possible is essential to provide a valid basis for hospital pandemic planning.

This modeling study is limited in several ways. Mayo Clinic is atypical with respect to its resources and capacities; therefore, its operational bottlenecks and capacities are different than most hospitals. However, we believe that the methodology (with appropriate inputs) would work for any hospital. To test this, a similar analysis should be conducted of a number of hospitals of different sizes and characteristics. Although considerable effort was made to ensure the accuracy of the input data, there is no independent way to verify it. Likewise, although the assumptions that were used were derived from the available literature or by consensus of the expert judgment of the researchers, they could be wrong. Finally, although extensively tested, some of the thousands of formulae in the model could contain inadvertent errors. Continued use should build confidence in the validity of the model.

Despite these limitations, we believe this model is significantly more useful than previous models (eg, FluAid,[20] FluSurge,[21] FluWorkLoss,[22] InfluSim,[6] PanViz,[23] and the AsiaFluCap Simulator[24]) because, through Monte Carlo Simulation, Panálysis allows for decision making with respect to uncertainty and the user's risk tolerance.

Considering projected patient demand, available resources, surge response options, operational constraints, and operational interrelationships, we successfully projected levels of key supplies needed for a wide range of pandemic scenarios that use up to 100% of Mayo Clinic's surge capacity of beds and ventilators. We displayed the probability of needing various supply levels across the spectrum of scenarios that were considered. Within the range of the projected supply values, there is no single right answer for the amount of supplies that should comprise Mayo Clinic's stockpile. Ultimately that is a management decision based on threat perception, risk tolerance, and cost. However, the model allows users to see how the stockpile needs of 1 resource relates to another, to easily recalculate needs based on changing assumptions or evidence, and to identify operational bottlenecks and to test different response tactics.

From our results, as illustrated in Figure 1, it is clear that the biggest return on investment for all resources is having some stockpile, even if it is relatively modest. In the example of oseltamivir, approximately half of the scenarios are covered by stockpiling the first 2,000 courses, but it would require an additional 6,000 courses to cover the remainder of iterations. Additionally, by identifying the system's limiting factors, cost-effectiveness and productivity-efficiency planning can occur to optimize output and eliminate waste.

CONCLUSIONS

We describe here a methodology for individual hospitals and hospital systems to make informed decisions about supply, pharmaceutical, and capacity planning needs for a severe influenza pandemic. This same methodology could be applied to any clinically important resource that can be counted and could be used for other disaster planning scenarios that would overwhelm normal hospital resources. The methodology could also be used as an emergency management tool during a crisis to aid in real-time decision making by using actual epidemiologic data of the emerging outbreak and changing resource data. This approach is scalable and by merging the findings from individual hospitals, it could be used by local, state, and federal authorities to plan across a state or across the nation.

Further studies are needed to understand how results vary in different hospital settings and to understand the economic feasibility of preparing for a given level of pandemic scenario probabilities. Additionally, although core direct patient care roles were included in the assessment as a basis for understanding resource needs, the lack of availability of nonclinical roles could significantly influence a hospital's ability to maximize patient care during an influenza pandemic.

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SUPPLEMENTARY DATA

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.ajic.2016.10.019.

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