Simple triage scoring system predicting death and the need for critical care resources for use during epidemics

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LEARNING OBJECTIVES

On completion of this article, the reader should be able to:

1. Identify the predictors of death during an epidemic.
2. Describe a model for predicting the need for intensive care unit care during an epidemic.
3. Create guidelines for use in a hospital.

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Objectives: **In the event of pandemic influenza, the number of critically ill victims will likely overwhelm critical care capacity. To date, no standardized method for allocating scarce resources when the number of patients in need far exceeds capacity exists. We sought to derive and validate such a triage scheme.**

Design: **Retrospective analysis of prospectively collected data.**

Setting: **Emergency departments of two urban tertiary care hospitals.**

Patients: **Three separate cohorts of emergency department patients with suspected infection, comprising a total of 5,133 patients.**

Interventions: **None.**

Measurements: **A triage decision rule for use in an epidemic was developed using only those vital signs and patient characteristics that were readily available at initial presentation to the emergency department. The triage schema was derived from a cohort at center 1, validated on a second cohort from center 1, and then validated on a third cohort of patients from center 2. The primary outcome for the analysis was in-hospital mortality. Secondary outcomes were intensive care unit admission and use of mechanical ventilation.**

Main Results: **Multiple logistic regression demonstrated the following as independent predictors of death: a) age of >65 yrs, b) altered mental status, c) respiratory rate of >30 breaths/min, d) low oxygen saturation, and e) shock index of >1 (heart rate > blood pressure). This model had an area under the receiver operating characteristic curve of 0.80 in the derivation set and 0.74 and 0.76 in the validation sets. When converted to a simple rule assigning 1 point per covariate, the discrimination of the model remained essentially unchanged. The model was equally effective at predicting need for intensive care unit admission and mechanical ventilation.**

Conclusions: **If, as expected, patient demand far exceeds the capability to provide critical care services in an epidemic, a fair and just system to allocate limited resources will be essential. The triage rule we have developed can serve as an initial guide for such a process. (Crit Care Med 2007; 35:1251–1256)**

KEY WORDS: triage; epidemic; avian influenza; mechanical ventilation; intensive care

Although H5N1 may well cause the next human influenza pandemic, its attack rate, virulence, and susceptibility to antivirals or vaccines remain uncertain. However, there is less uncertainty that—if the next influenza pandemic is severe—the number of critically ill victims will overwhelm most communities' traditional inpatient and critical care capacity. To assist hospitals in preparing and responding to such events requiring large surges in critical care capacity, the Working Group on Emergency Mass Critical Care (1) promulgated a set of recommendations. One of the major recommendations was for healthcare organizations to have a standardized method for allocating scarce resources (e.g., mechani-

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All authors had full access to all of the data in the study and take responsibility for the integrity of the data and the accuracy of the data analysis.

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cal ventilators) when the number of patients in need far exceeds available capacity. The Working Group advocated for distribution of resources to be guided by patients' likelihood to benefit. Subsequently, Rubinson and O'Toole (2) proposed development of a simple, physiologic-based triage algorithm. To date, no such validated algorithm exists.

The concept of triage during medical catastrophes is not new (3). Multiple triage algorithms exist for mass-casualty traumatic incidents (4). Unfortunately, these algorithms may have little, if any, utility during pandemic influenza because they were not designed to categorize the likelihood of survival for patients with medical critical illness. In addition, an evidence-based triage algorithm derived from previous pandemic influenza outbreaks is unlikely to be developed. Clinical data from severe pandemics are limited or missing, and the provision of critical care services has markedly changed during the past decades, so outcomes may be very different now. Indeed, despite all of the pandemic influenza preparedness activities, there is still insufficient guidance for clinicians to accurately and fairly prioritize patients in the hope of distributing scarce resources to optimize survival for the largest number of patients during a serious pandemic.

Several severity of illness scores have been developed to predict intensive care unit (ICU) or hospital mortality for medical patients in ICUs (5–7). These scoring systems are generally not used for everyday ICU triage because they better stratify the risk of death for *populations* rather than *individuals*. They also have only moderate discriminating ability at ICU admission and even within the first day of ICU care (8, 9). Furthermore, many ICU scoring systems do not perform adequately using emergency department (ED) data, especially when a number of required laboratory measurements are not immediately available (10)—situations that will be even more relevant during a pandemic. Clinicians who frequently care for medical, critically ill patients may perform better than scoring systems at predicting mortality from data gleaned within the first 24 hrs of ICU admission, yet their accuracy is still limited (8). Hence, there remains an urgent need for a novel method to triage medical, critically ill patients during a pandemic.

Hick and O'Laughlin (11) recently published a tiered approach to allocation of mechanical ventilators during a medical catastrophe. These strategies, although an excellent initial attempt to tackle this difficult topic, were theoretically derived and promulgated without validation of their rationing scheme. A similar, tiered approach, using a combination of patient history and the established Sequential Organ Failure Assessment (SOFA) score, has been proposed by the Ontario Health Plan for an Influenza Pandemic Working Group (12). As an alternative approach, we derived a triage scoring system from cohorts of patients with suspected infection presenting to the ED during nonpandemic situations. Clearly, not all clinical features of common infections are similar to H5N1 influenza, and treatment may differ. However, most severe infections result in similar organ dysfunctions (e.g., acute respiratory distress syndrome and severe sepsis) as those described with the current human cases of H5N1 influenza (13). Thus, the objective of this study is to derive and both internally and externally validate a simple triage risk-stratification tool that predicts the primary outcome of mortality, in addition to the need for mechanical ventilation and treatment in an ICU, in patients presenting to the ED with infection.

METHODS

This is a secondary analysis of three separate prospectively identified and collected cohorts of ED patients with suspected infection. To develop the triage decision rule, only those vital signs and additional patient characteristics that were readily available at initial patient presentation to the ED were evaluated. The triage schema was derived from a cohort at center 1 (Beth Israel Deaconess Medical Center), validated on a second cohort from center 1, and then externally validated on a third cohort of patients from center 2 (Carolinas' Medical Center). Institutional review board approval was obtained for data collection from both institutions.

Assembly of Patients

Cohort 1: Derivation Set. The methods for assembly of cohort 1 have been described previously (14). In brief, this cohort included all consecutive adult patients (≥18 yrs old) presenting with suspected infection between February 1, 2000, and February 1, 2001, to the ED of Beth Israel Deaconess Medical Center, an urban academic medical center with approximately 50,000 annual ED visits. Patients were classified as "suspected infection" by the surrogate marker of the clinical decision to obtain a blood culture. Both patients admitted to the hospital and those discharged from the ED were included in this cohort. To exclude patients with possible surgical pathogeneses that would not be pertinent to this investigation, patients were excluded if their suspected source of infection was intra-abdominal.

Cohort 2: Internal Validation Set. This cohort included all consecutive adult patients (≥18 yrs old) presenting to the ED of Beth Israel Deaconess Medical Center with suspected infection between December 10, 2003, and September 30, 2004. Patients were identified by a daily screening of the ED admission log. Any patient with a complaint of suspected infection (e.g., pneumonia) or possible infection (e.g., shortness of breath) was identified for a confirmatory chart review. If the diagnostic testing in the ED or the medical decision making section of the patient chart indicated a suspected infection, then that patient was included in the study. Chart review included only the ED experience and occurred without knowledge of subsequent hospital course. Exclusion criteria included patients with a suspected intra-abdominal infection and those sent home from the ED; thus, this cohort consists of patients admitted to the hospital only.

Cohort 3: External Validation Set. The external validation cohort was enrolled from the ED at Carolinas' Medical Center, an 800-bed teaching and tertiary referral hospital with >100,000 patient visits per year. Included were adult patients (≥18 yrs old) admitted to the hospital from the ED. Patients were enrolled between July 2004 and June 2005 and divided into four blocks. Enrollment took place during 24-hr periods, chosen from a standard random sample of 24-hr periods (12 am to 12 am), comprising one half of the number of days in each block. Patient diagnoses were reviewed *post hoc*, and patients were included in this cohort if they had a principle diagnosis of an infectious pathogenesis as the reason for the index hospitalization. Similar to the Beth Israel Deaconess Medical Center cohorts, patients with a suspected intra-abdominal infectious pathogenesis that required surgical intervention were excluded.

Data Collection and Eligible Covariates

Pertinent demographics, triage vital signs, and components of the history and physical exam were collected. Only covariates that could be easily assessed at triage were eligible for inclusion in the triage score. Vital signs included heart rate, systolic blood pressure, respiratory rate, and oxygen saturation. Altered mental status was considered present if evidence of altered mentation was documented in the physician note or if the patient

Table 1. Patient characteristics in the derivation and validation sets

	Center 1 Derivation (n = 3206)	Center 1 Internal Validation (n = 1,118)	Center 2 External Validation (n = 809)
Age in years, mean ± SD	60 ± 20	64 ± 19	54 ± 19
Male sex, %	47	49	52
Co-morbid conditions, %			
Cerebrovascular disease	9	11	8
Congestive heart failure	15	18	9
Diabetes	23	31	25
HIV	7	5	13
Malignancy	20	15	6
Altered mental status	21	14	10
HR, beats/min (mean ± SD)	94 ± 21	93 ± 22	101 ± 22
SBP, mm Hg (mean ± SD)	129 ± 28	133 ± 31	128 ± 29
Shock index, mean ± SD	0.77 ± 0.26	0.75 ± 0.28	0.82 ± 0.27
Respiratory rate, breaths/min (mean ± SD)	20 ± 5.9	20 ± 5.7	21 ± 6.2
Pulse oximetry, % (mean ± SD)	94 ± 8	96 ± 5	90 ± 24
Hospitalization outcomes, %			
Intubated	4	13	4
ICU admission	12	22	15
Mortality	5	7	6
Suspected source of infection, n (%)			
Respiratory	854 (27)	292 (26)	257 (32)
Urogenital	347 (11)	132 (14)	110 (14)
Skin/soft tissue	675 (21)	225 (23)	138 (17)
CSF	89 (3)	8 (1)	18 (2)
Suspect bacteremia	210 (7)	28 (3.4)	108 (13)
Fever without a source	487 (15)	83 (9)	23 (3)
Other/unknown	614 (19)	220 (23)	155 (19)

HIV, human immunodeficiency virus; HR, heart rate; SBP, systolic blood pressure; ICU, intensive care unit; CSF, cerebrospinal fluid.

had a documented Glasgow Coma Score of <15. For inclusion as a covariate in the score, the vital signs were dichotomized at logical cut points. Heart rate was assessed at the thresholds of 90, 100, and 120 beats/min; systolic blood pressure at 90 and 100 mm Hg; and respiratory rate at 20, 30, and 40 breaths/min. The presence of hypoxemia was defined as an initial oxygen saturation of <90%, patient requirement for endotracheal intubation, or the presence of an oxygen saturation of <93% while receiving supplemental oxygen. Shock index (shock index = heart rate/systolic blood pressure) was assessed at 1.0 and 0.9. Age was examined at the thresholds of 65, 75, and 85 yrs of age.

Definition of Outcomes

The primary outcome for the analysis was in-hospital mortality. Any patient surviving to hospital discharge was considered "alive" for this analysis. Secondary outcomes were intensive care admission at any point during hospitalization and use of mechanical ventilation. These outcomes were selected to represent resources likely to be limited during an influenza pandemic or other large-scale epidemic.

Statistical Methods

Covariates were first assessed in univariate analyses using death as the dependent variable. Covariates that achieved a univariate significance at a threshold of $p < .1$ were subsequently eligible for inclusion in a multivariable logistic-regression model, which was used as the cut-off for inclusion in the final model. The final model was built to predict mortality using forward selection, backward selection, and stepwise. All approaches resulted in a uniform final model. Two scores were then created, one using a weighted system by dividing the beta-coefficients by a common denominator to obtain an integer score proportional to the magnitude of the beta-coefficient and the other assigned 1 point per covariate. Ultimately, both rules performed in a similar fashion, so the simpler 1 point per covariate method was selected as the final rule for ease of application at triage. The performance of the rule was assessed by calculating the area under the receiver operating characteristic curve. The model was derived on cohort 1 and then validated separately on cohorts 2 and 3. Next, the rule was assessed to predict secondary outcomes of ICU usage and mechanical ventilation—the rule was not re-derived for these outcomes; instead, the rule derived from mortality outcomes was used.

RESULTS

There were a total of 5,133 patients included in the study: 3,206 in the derivation cohort (site 1), 1,118 in the internal validation cohort (site 1), and 809 in the external validation cohort (site 2). The mortality rates were 4.7%, 6.6%, and 6.3%, respectively. The prevalence of the secondary outcomes was: 3.8%, 13%, and 4.0% for intubation and 12%, 22%, and 15% for admission to the ICU. Patient characteristics are shown in Table 1.

Multiple logistic regression demonstrated the following as independent predictors of death: a) age of >65 yrs, b) altered mental status, c) respiratory rate of >30 breaths/min, d) low oxygen saturation, and e) shock index of >1 (heart rate > blood pressure) (Table 2). This model had an area under the receiver operating characteristic curve (AUC) of 0.80, and when converted to a simple rule assigning 1 point per covariate, the discrimination of the model remained essentially unchanged, with an AUC of 0.79. We assessed another model by using assigned points based on each covariate's beta coefficient, but it yielded a very similar AUC. We therefore selected the simpler model. Four logical groupings, with increasing points, were created and had the following mortality rates in the derivation cohort: very low risk (0 points), 0.4% mortality (95% confidence interval,

0.1–0.8%); low risk (1 point), 8.8% mortality (2.6–4.6%); moderate risk (2 points), (6.5–11.0%); and high risk (≥3 points), 25% mortality (19–31%) (Table 2, Fig. 1*A*). Although not derived specifically to predict the secondary outcomes of need for admission to an ICU and requirement of mechanical ventilation, the rule also worked reasonably well in predicting these secondary outcomes (Tables 3 and 4, Fig. 1, *B* and *C*).

When the triage rule was validated on the internal validation cohort, the overall AUC for the score as a predictor of death was 0.76 (Table 4). As the score increased, mortality also increased in a fashion similar to the derivation cohort (Fig. 1*A*). Similarly, the score was less precise but still predictive of the need for admission to an ICU and mechanical ventilation, with an AUC of 0.72 and 0.73, respectively (Fig. 1, *B* and *C*).

Results from the external validation also support the rule's performance (Table 3, Fig. 1*A*). The AUC for the rule as a predictor of death was 0.73. As expected, in a different center, the AUC of the rule was less, although the rule still significantly predicted outcome (Fig. 1, *B* and *C*). In the external validation cohort, the rule's AUC for need for ICU admission was 0.70 and for mechanical ventilation was 0.68.

DISCUSSION

We have demonstrated that a simple rule—using only variables readily available at ED triage—risk stratifies patients who present to the ED with suspected infection. Using a combination of a) age of >65 yrs, b) altered mental status, c) respiratory rate of >30 breaths/min, d) low oxygen saturation, and e) shock index of >1 (heart rate > blood pressure), patients may be categorized according to likelihood of survival with hospitalization. Although not designed to do so, these categories also predict, reasonably well, consumption of hospital critical care resources, specifically, of critical care beds and mechanical ventilators. The strength of our study lies in the large, prospectively collected cohorts of patients, on whom the rule was developed and both internally and externally validated. There is an inherent weakness in the rule in that it was not created using patients presenting to the hospital during an epidemic; however, we submit that our populations of ED patients with suspected infection represent reasonable surrogates for our "proof-of-concept" triage rule.

Experts at the World Health Organization and elsewhere believe that the world is now closer to another influenza pandemic than at any time since 1968, when the last pandemic occurred. If a severe human influenza pandemic occurs, it is likely that many people will develop serious or critical illness due to insufficient, immediately available vaccines and effective antivirals (15). Even in developed countries with modern healthcare infrastructures, there is little capability to expand hospital capacity, and particularly critical care capacity, to meet the surge in critical care demand that would be expected during a pandemic. During the recent severe acute respiratory syndrome (SARS) epidemic, relatively few acutely ill patients (370 suspected and confirmed cases in 4 months) strained the resources of the health system in Toronto. In fact, surge capacity actually decreased at points of the outbreak due to ICU and ED closures (16). During a severe influenza pandemic, it may be impossible to maintain traditional hospital and clinical standards of care. Even if the commerce infrastructure is maintained, extreme shortages of healthcare professionals and medical equipment may well occur. Hence, if patient demand far exceeds the capability to provide needed medical services, a fair and just system to allocate limited resources will be essential. The triage rule we have developed can serve as an initial guide for such a process.

How would our model be operationalized and incorporated into existing triage

Table 2. Independent predictors of mortality identified by multivariate analysis

Variable	Odds Ratio	95% CI	Complex Rule Points	Simplified (Final) Rule Points
Respiratory rate of >30 breaths/min	3.9	2.5 to 6.3	4	1
Shock index > 1 (HR > BP)	2.8	1.8 to 4.2	3	1
Low oxygen saturation	2.8	1.8 to 4.2	3	1
Altered mental status	1.9	1.3 to 2.8	2	1
Age of 65–74 yrs	3.0	1.7 to 5.5	3	1
Age of ≥75 yrs	4.4	2.7 to 7.2	4	1

CI, confidence interval; HR, heart rate; BP, blood pressure.

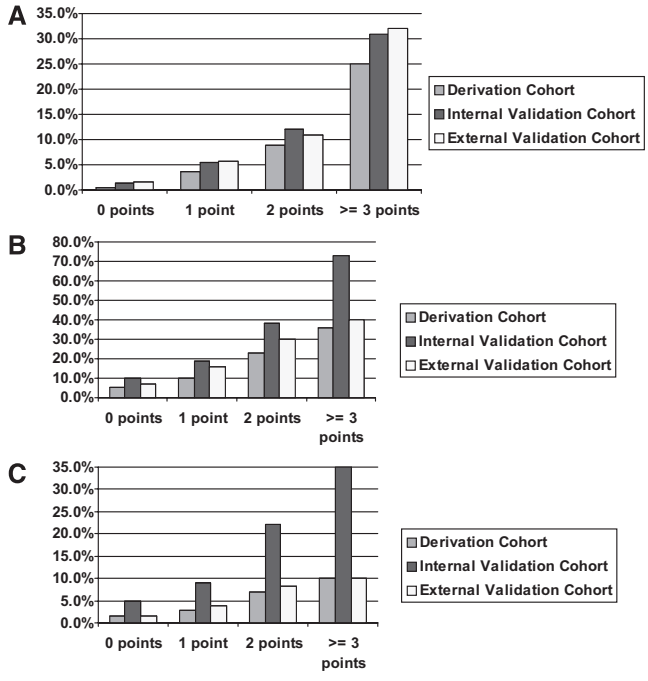

Figure 1. Discrimination of the rule in predicting death (*A*); discrimination of the rule in predicting need for intensive care unit admission (*B*); discrimination of the rule in predicting need for mechanical ventilation (*C*).

Table 3. Performance of the rule

Variable	Derivation (%)	Internal Validation (%)	External Validation (%)
Mortality, points			
0	5/1144 (0.4)	5/396 (1.3)	6/357 (1.7)
1	45/1257 (3.6)	26/477 (5.5)	16/282 (5.7)
2	54/617 (8.8)	21/174 (12)	13/120 (11)
≥3	47/188 (25)	22/71 (31)	16/50 (32)
Need for intensive care, points			
0	61/1144 (5.3)	39/396 (9.9)	25/357 (7.0)
1	124/1257 (9.9)	90/477 (19)	44/282 (16)
2	140/617 (23)	67/174 (39)	36/120 (30)
≥3	68/188 (36)	52/71 (73)	20/50 (40)
Need for mechanical ventilation, points			
0	18/144 (1.6)	20/396 (5.1)	6/357 (1.7)
1	37/1257 (2.9)	43/477 (9.0)	11/282 (3.9)
2	43/617 (7.0)	38/174 (22)	10/120 (8.3)
≥3	25/188 (13)	40/71 (56)	5/50 (10)

Table 4. Area under the receiver operating characteristic curves for the different cohorts and outcomes

	n	Mortality	ICU Admission	Ventilatory Requirement
Site 1: derivation	3906	0.80	0.70	0.69
Site 1: validation	1118	0.76	0.72	0.73
Site 2: validation	809	0.73	0.70	0.68

ICU, intensive care unit.

This table shows the different area under the curves for each of the cohorts and the different outcomes. The rule was built primarily for the mortality outcome but has validity for the secondary outcomes as well.

frameworks? Because supportive care is similar regardless of cause of respiratory failure and sepsis, we believe that developing an initial algorithm based on existing cohorts of patients with suspected infection is the best way to provisionally develop a triage algorithm for a future infectious pandemic. As time passes during a pandemic, the triage rule can and will need to be refined. At the beginning of a pandemic, medical care may continue at the usual standard for the given region. As an epidemic expands and the mismatch of resources and demand for care worsens, a decision on the need for patient triage would need to occur. Such a decision would need to be taken on a regional basis, with input from all of the stakeholders in the community (1, 11). Our model provides an appropriate starting point for such a system of triage. As the event progresses, the model would be further modified based on available resources and operational research.

We have deliberately excluded the patient's medical history from the variables included in the analysis. Other proposed schemes have included such information (11, 12). We believe that it will be logistically difficult to accurately assess these data during an overwhelming catastrophe. Patients are not likely to arrive at the hospital with their medical records, triaging physicians are not going to have time to search for the patients' records, and once it becomes clear that triage of patients based on medical history is taking place, patients are unlikely to volunteer truthful information. Similarly, although both Hick and O'Laughlin (11) and the Ontario Working Group (12) have included laboratory testing within their triage schemes, we have excluded laboratory testing from our algorithm. Such testing will be resource intensive and will unnecessarily delay triage decisions in a mass-casualty setting. In addition, the use of these laboratory results, either individually or as components of ICU scoring systems, has not been validated in patients presenting to the ED with infection. However, if point-of-care testing of strong, validated, laboratory predictors of mortality, such as lactate, are made available, these may be reasonable supplements to clinical triage rules such as ours (17).

The Working Group on Emergency Mass Critical Care (1) recommended uniform application of triage to all patients in the hospital, rather than just victims of the outbreak. A sophisticated schema will ultimately need to be developed for decisions regarding initiating, withholding, and withdrawing potentially life-saving scarce resources. We chose to focus on triage at entrance of the patient into the medical system, where initiation and withholding of care decisions will be initially determined. We envision that if the pandemic is so severe that those in need far outnumber available resources, 1) many communities will be affected concurrently, evacuation to a distant region will not be feasible, and deployment of sufficient medical resources from external resources will be limited, 2) nonhospital locations may be used to screen patients for medical needs, 3) laboratory and radiographic studies may not be readily available for many patients requiring triage, and 4) not all patients will be able to get a trial of critical care to see if they benefit due to resource limitations. A triage algorithm based on data readily available at medical system presentation that could help predict severity of illness and expected need for scarce critical care resources would be an invaluable tool.

To design successful triage systems, protocols must be developed, validated, and available before a crisis. Input is required from many stakeholders, including community members, emergency management officials, hospital officials, critical care experts, public health officials, and ethicists. Such protocols need to be applied in a standardized and fair process for all patients. Ultimately, there are difficult ethical decisions that may need to be made. Protocols, developed during the course of usual healthcare system operations, will obviously represent the "best case" scenario for patient survival. As an epidemic progresses and the requirement for healthcare resources outstrips the available resources, patient care is likely to be further degraded. In such an event it is likely that this prediction rule will need modification. For these reasons, the rule we present is only a starting point.

Our study has several limitations. First, this model is derived on patients arriving to the ED with a variety of infectious diseases. Most of these conditions have a mortality rate less than that of avian influenza, and although both conditions are manifested by the immune

system's inflammatory response, there are still important differences in the biology of the disease states. The reported case fatality rates for avian influenza are between 33% and 100% (13). This high mortality indicates that our model would err on the conservative side. In addition, the rule may perform differently with a respiratory-based illness than in our population comprising a heterogeneous set of infectious diseases. Similarly, the average ages in our three cohorts are between 54 and 64 yrs, and age of >65 is a predictor of mortality in our schema. The limited available evidence suggests that the attack rate and mortality rates for avian influenza are higher in younger populations (13). For all of these reasons, it will be important to revalidate any triage model at the outbreak of an epidemic and continuously throughout.

The second major limitation of our study is that, although we have validated the model in two centers and three time periods, there may be populations or healthcare systems in which the model performs differently. Notably, our site 1 validation population had higher rates of outcome; the reason for this is that it was an inpatient population only, compared with the initial and site 2 validation cohorts, which were both inpatients and outpatients. Any model of triage should be validated in the population it is meant to serve, and we would encourage healthcare systems outside of the United States to validate our model within their system.

Finally, patients with severe illness, who might have benefited from usual hospital care, will be found to be beyond rescue within the constraints of an epidemic. Provision must be made for palliative care for patients for whom critical care services have been withheld or withdrawn.

In summary, we present a triage rule for use during an epidemic. This rule was derived using actual data from patients presenting to the ED with suspected infection. Although the rule will need modification or validation in the future using data from a real pandemic, it provides a starting point for an organized triage system for use during such an event.

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