# Simulation of Ventilator Allocation Strategies During the COVID-19 Pandemic

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# Abstract

As the number of SARS-CoV-2 infections mount globally, hospital systems face unprecedented demands on limited resources, including ventilators. Existing ventilator allocation strategies have not undergone rigorous analyses to evaluate their real-world implications. To address this critical gap in knowledge with profound societal implications, we present a simulation model to evaluate the proposed allocation strategies and report the trade-offs between these strategies that merit careful consideration.


# Introduction, Results And Discussion

The COVID-19 pandemic is overwhelming healthcare systems around the world. The number of available ventilators currently falls far short of the anticipated need by tens or even hundreds of thousands in the United States and elsewhere.[1] Given this dire reality, there is consensus that institutions should establish algorithmic patient ranking systems to allocate ventilators rather than compel subjective rationing decisions to be made at the bedside.[1,2]

Proposed ventilator allocations systems have uniformly abandoned the “first-come, first serve” and “sickest-first” principles and moved to utilitarian considerations of maximization of benefits for the population.[1,2] There is no consensus, however, on whether benefit maximization should focus on lives saved or life-years saved and to what extent benefit maximization should be constrained by the ethical value of treating people equally.[1,2] Some advocate that younger patients should be prioritized to ensure as many achieve a “complete life” as possible,[3] while others argue that age should not be used as an explicit factor in allocation at all.[1]

As a result, there is considerable variation in the translation of these ethical principles into concrete triage rules. For example, early reports and guidelines from Italy suggest physicians are employing age cutoffs.[4,5] New York state guidelines categorize patients needing mechanical ventilation into three priority tiers based on the Sequential Organ Failure Assessment (SOFA) score and use a lottery to break ties within tiers; age is explicitly ignored.[6] Another proposed priority score from researchers at the University of Pittsburg would linearly assign the patient 1-4 points from three different categories: SOFA, medical comorbidities, and age.[2] Maryland’s state proposal would give patients a score ranging from 1-8 based on SOFA and comorbidities, using age as only a tiebreaker.[7] Each of these varying formulas represents the mathematical summarization of a nuanced ethical framework. The ethical consequences of applying specific triage rules to a complex system like ventilator allocation can be better appreciated with simulation modeling.

We developed a simulation model to illustrate the downstream consequences of different triage rules under varying conditions of patient volume, patient severity of illness, and ventilator availability. The model draws a patient sample from the age distribution of COVID-19-infected patients as reported by the Centers for Disease Control[8] and the distribution of SOFA score and comorbidities at the time of

intubation derived from a large tertiary care hospital system.[9] As recommended by the corresponding priority scores,[2,10] chronic disease categorization (none, major, severe) was assigned based on the presence of qualifying diagnoses and the value of the AHRQ Elixhauser Co-morbidity Index Score for in-hospital mortality.[11] The model then simulates patient survival with ventilation based on the calibration of the SOFA score in a multi-center cohort of over 180,000 critically ill patients with infections.[12] The life-years saved by each model was calculated by subtracting the patient's age from one hundred (maximum lifespan). Life-years saved were discounted 50% if a major chronic disease was present and reduced to one if a severe chronic condition was present. We applied eight different ventilator allocation rules to this population as described in detail in **Table 1**.

Our simulation model (**Figure 1**) demonstrates that: 1) Any triage system that incorporates age, SOFA or comorbidities would result in more lives and life-years saved than a simple lottery allocation system; 2) Youngest first system results in more life-years saved but less total lives saved compared to methods incorporating SOFA and comorbidities (Maryland and Pittsburgh); 3) Multi-principle systems incorporating age, SOFA and comorbidities have better performance in both lives and life-years saved than New York's SOFA tier system. Importantly, there is much wider variation between the allocation systems in terms of life-years saved compared to lives saved.

Given the ethical complexity of these decisions, no ventilator allocation system will be universally satisfactory. A difficult balance between competing ethical principles must be struck. Simulation modeling provides physicians, ethicists, and other stakeholders a deeper understanding of the intended and unintended consequences of different allocation rules. This will enable policymakers to evaluate the trade-offs involved in a transparent and detailed manner. Our simulation model is not intended to be a comprehensive representation of allocation, but rather an open-source tool to illustrate the potential effects of different triage rules. More comprehensive models that simulate the dynamic flow of patients into different hospital systems should be developed. Policymakers should integrate the power of simulation modeling with traditional ethical reasoning when faced with the difficult choices inherent in ventilator allocation.

**Table 1: Simulated outcomes under different ventilator triage rules**

| System | Description | Mean Lives Saved (N = 1,000) | Mean Life-years Saved (N = 31,827) |
|---|---|---|---|
| Sickest First | Highest SOFA score first | 315 (31) | 10219 (32) |
| Lottery | Random assignment | 368 (37) | 11784 (37) |
| New York | SOFA tiers with random assignment within tiers (SOFA<7, SOFA 8-11, SOFA>11) | 407 (41) | 13243 (42) |
| Maryland | SOFA tiers with additional points for severe comorbidity; age used as tie-breaker within tiers (SOFA<9, SOFA 9-11, SOFA 12-14, SOFA>14) | 415 (41) | 15342 (48) |
| Pittsburgh | SOFA tiers with additional points for major or severe comorbidity; age used as tie-breaker within tiers (SOFA<6, SOFA 6-8, SOFA 9-11, SOFA>11) | 396 (40) | 15967 (50) |
| Youngest First | Prioritizing patients solely based on age | 370 (37) | 15773 (50) |
| Maximize Lives Saved | Prioritizing patients using SOFA as a continuous variable instead of a tier-system. | 421 (42) | 14292 (45) |
| Maximize Life-years Saved | Prioritizing patients based on a combination of age and SOFA as a continuous variable | 391 (39) | 17332 (54) |

Results of 10,000 simulation runs under each triage rule for 500 ventilators allocated to 1,000 patients. Patient characteristics were drawn from the CDC reported age distribution of COVID-19 patients and SOFA and comorbidity distribution from a large tertiary care hospital system. Lives saved and life-years saved are presented as N (%).

# Methods

We developed a simulation model to illustrate the downstream consequences of different triage rules under varying conditions of patient volume, patient severity of illness, and ventilator availability. The model is available online for users to test with varying numbers of patients, ventilators and different allocation strategies:

https://wparker-uchicago.shinyapps.io/ventilator_allocation/.

For this study, we set the conditions to 1,000 patients with 500 available ventilators to simulate severe scarcity across a regional area (i.e., multiple hospitals across a city). The model created a simulated dataset of 1,000 patients and their characteristics (age, comorbidity burden and SOFA score). The age of these patients were sampled from the age distribution of COVID-19-infected patients as reported by the Centers for Disease Control.[8]

The relationships between age, comorbidities and SOFA score for these simulated patients were derived from a large tertiary care hospital system.[9] Based on general impracticability and minimal harm, waivers of consent were granted by the University of Chicago Institutional Review for this study. As the majority of ICU patients during this pandemic would be patients with respiratory failure secondary to COVID-19 infection, the clinical data was sampled from patients with evidence of infection and respiratory failure requiring intubation. Of the 262,937 inpatient admissions, 2,661 patients met this criteria and were included in the analyses. Clinical characteristics of this cohort are presented in **Methods Table 1**. The comorbidity burden for these patients was categorized as none, major or severe based on a combination of currently utilized priority scores[2,10] and the value of the AHRQ Elixhauser Co-morbidity Index Score.[11] A multinomial logistic regression was performed on age to comorbidity burden, and then linear regression was done to regress the SOFA score on the age and comorbidity burden of the patients. The coefficients from these regressions are presented in **Methods Table 2**. These relationships between age, comorbidity burden and SOFA were used to simulate patient data for the simulation model.

We applied eight different ventilator allocation rules to the simulated population, and these allocation rules are described in further detail in Table 1 in the manuscript. If the allocation rule assigned a patient to a ventilator, the model then determined patient survival based on the calibration of the SOFA score to survival from a multi-center cohort of over 180,000 critically ill patients with infections.[12] If the patient survived, the life-years saved was determined by subtracting the patient's age from one hundred (maximum lifespan). Life-years saved was discounted by 50% if a major chronic disease is present. Since the definition of severe chronic condition in allocation scores is an expected lifespan of one year, the life-years saved was reduced to one if such a condition was present. If the allocation rule did not assign a patient to a ventilator, the patient did not survive. The simulation was repeated for 10,000 runs. Lives saved and life-years saved were averaged over the 10,000 runs and compared across the different allocation strategies.

The simulated data used age, comorbidity and SOFA score relationships based on clinical data from a single medical center. In order to make the simulation more generalizable and widely available, we have released the open-source code. The open-source nature of the annotated code allows users to tailor the age, comorbidity, and SOFA distributions of the patient population based on local institutional data. Our simulation model is not intended to be a comprehensive representation of allocation, but rather an open-source tool to illustrate the potential effects of different triage rules.

Methods Table 1. Clinical characteristics of mechanically ventilated patients used to simulate patient data.

| | Total population (n=2,661) |
|---|---|
| Age mean (SD) | 61 (16) |
| Gender n (%) | |
| Female | 1359 (51) |
| Male | 1302 (49) |
| Race n (%) | |
| White | 465 (17) |
| Black | 2025 (76) |
| Other | 171 (6) |
| Number of co-morbidities median (IQR) | 2 (0-6) |
| Elixhauser co-morbidities n (%) | |
| Congestive heart failure | 590 (22) |
| Valvular disease | 184 (7) |
| Pulmonary circulatory disorders | 189 (7) |
| Peripheral vascular disease | 245 (9) |
| Hypertension, uncomplicated | 1047 (39) |
| Hypertension, complicated | 447 (17) |
| Paraplegia | 116 (4) |
| Other neurological disorders | 260 (10) |
| Chronic pulmonary disease | 489 (18) |
| Diabetes, uncomplicated | 537 (20) |
| Diabetes, complicated | 212 (8) |
| Hypothyroidism | 211 (8) |
| Renal failure | 521 (20) |
| Liver disease | 197 (7) |
| Peptic ulcer disease | 26 (1) |
| AIDS/HIV | 14 (0.5) |
| Lymphoma | 77 (3) |
| Metastatic cancer | 188 (7) |
| Solid tumor without metastasis | 334 (13) |
| Rheumatoid arthritis/collagen vascular disease | 104 (4) |
| Coagulopathy | 374 (14) |
| Obesity | 242 (9) |
| Weight loss | 400 (15) |
| Fluid and electrolyte disorders | 804 (30) |
| Blood loss anemia | 111 (4) |
| Deficiency anemia | 95 (4) |
| Alcohol abuse | 148 (6) |
| Drug abuse | 135 (5) |
| Psychosis | 178 (7) |
| Depression | 268 (10) |
| SOFA at time of intubation median (IQR) | 7 (6-9) |
| Maximum SOFA score median (IQR) | 10 (8-13) |
| Duration of intubation, hours median (IQR) | 38 (14-90) |
| LOS, days median (IQR) | 9 (5-17) |

| | |
|---|---|
| **Mortality** n (%) | 833 (31) |

Methods Table 2. Regression coefficients for relationships between age, comorbidity burden, and SOFA scores.

| | Coefficient | Description |
|---|---|---|
| **Comorbidity ~ Age** | | |
| None | - | Reference |
| Major intercept | -0.783942 | Log odds of having major comorbidity compared to none |
| slope | .0066036 | Increase in log odds of having major comorbidity compared to none with each year increase in age |
| Severe intercept | -2.398532 | Log odds of having severe comorbidity compared to none |
| slope | .0128016 | Increase in log odds of having severe comorbidity compared to none with each year increase in age |
| **SOFA ~ Age + Comorbidity** | | |
| Intercept | 7.008651 | Intercept of SOFA score |
| Age | .0066036 | Increase in SOFA score per year increase in age |
| Comorbidity | | |
| None | - | Reference |
| Major | .0603057 | Increase in SOFA score for major comorbidity compared to none |
| Severe | .6066374 | Increase in SOFA score for severe comorbidity compared to none |

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# Figures

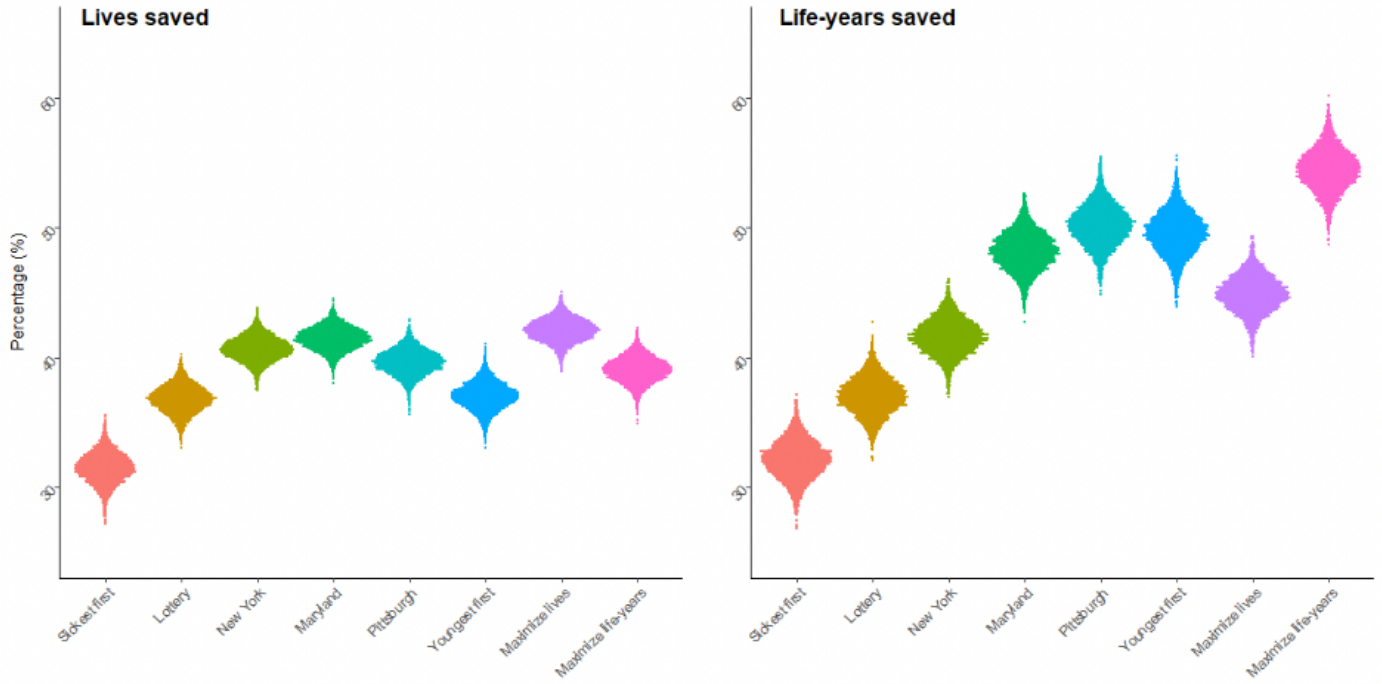


**Figure 1**

Simulated outcomes under different ventilator triage rules. Results from 10,000 simulations of each of the ventilator triage rules applied to the allocation of 500 ventilators to 1,000 patients. Patient characteristics were drawn from the CDC reported age distribution of COVID-19 patients, and the SOFA and comorbidity distribution from a large tertiary care hospital system. The x-axis is the allocation triage rule, and each point represents the resulting lives or life-years saved in each of the 10,000 simulation runs.

# Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- 2521310addinfo0q8w18d.txt
- Appendix.docx