SAND2020-4944PE

Treatment Model Design and Use

06 April 2020

SNL Pandemic Modeling Team

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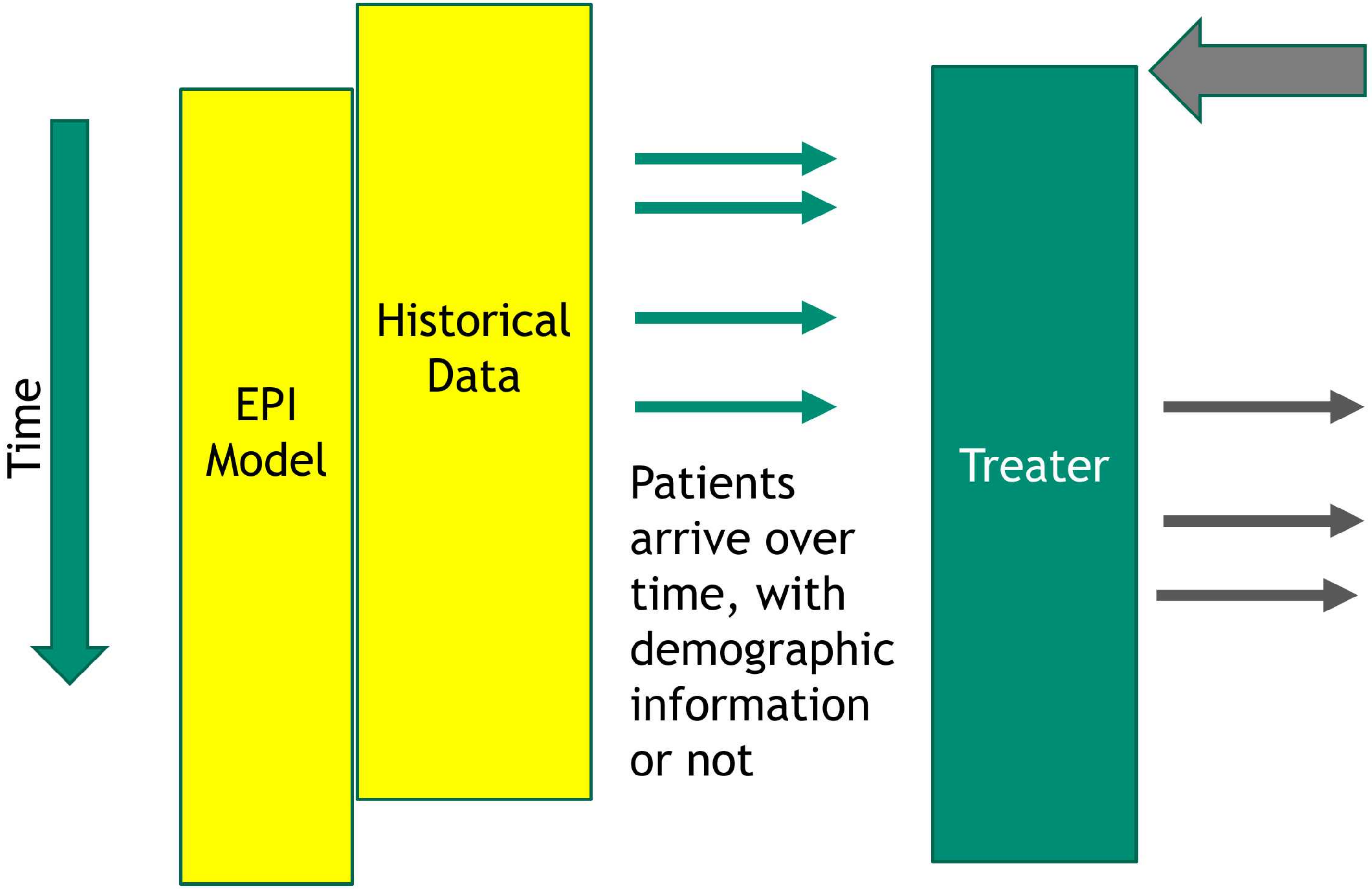
SAND2020-3836 PE

Model Formulation

Estimates maximum/cumulative resource use from patient flow data



Configuration information includes
- Possible treatment trajectories
- Kind of resources to track
- How fixed, human, and consumable resource are used

Max and cumulative resource use can be polled whenever

Can represent any scale of system
Many instances can be defined (e.g. county or individual hospitals)

Patient feeds from models, history, …

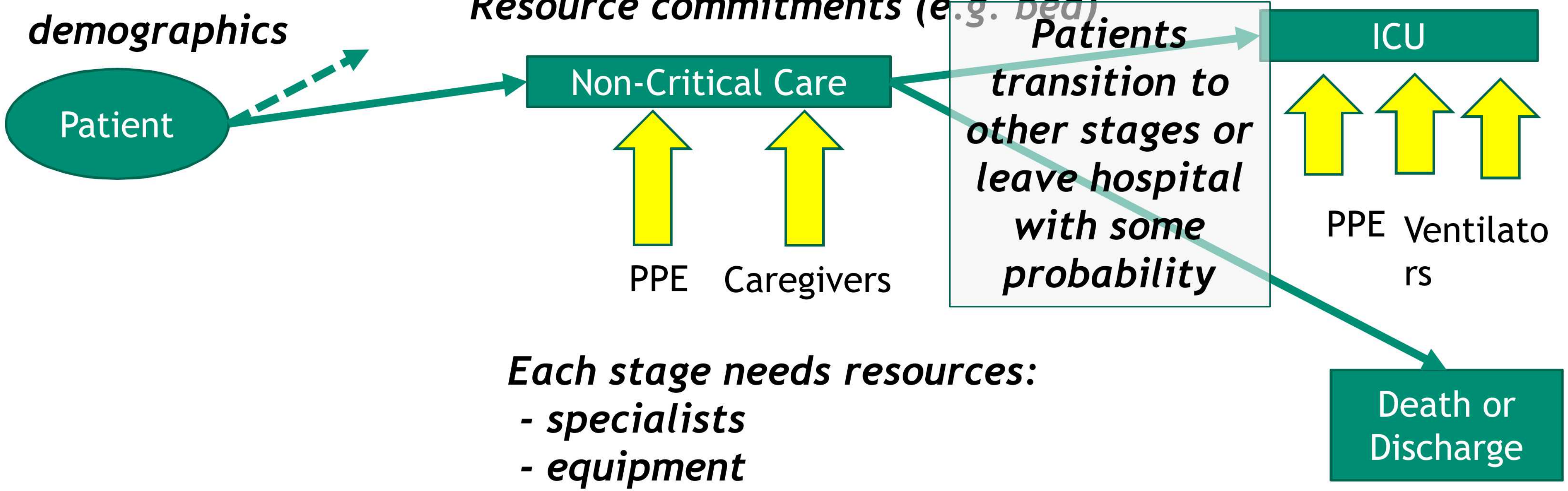
Implemented as a Java class and as web service

Treatment processes model processes and components

Patients take one of several possible paths, potentially based on demographics

Each path is made of one or more stages

Each stage has
minimum and maximum time
Resource commitments (e.g. bed)

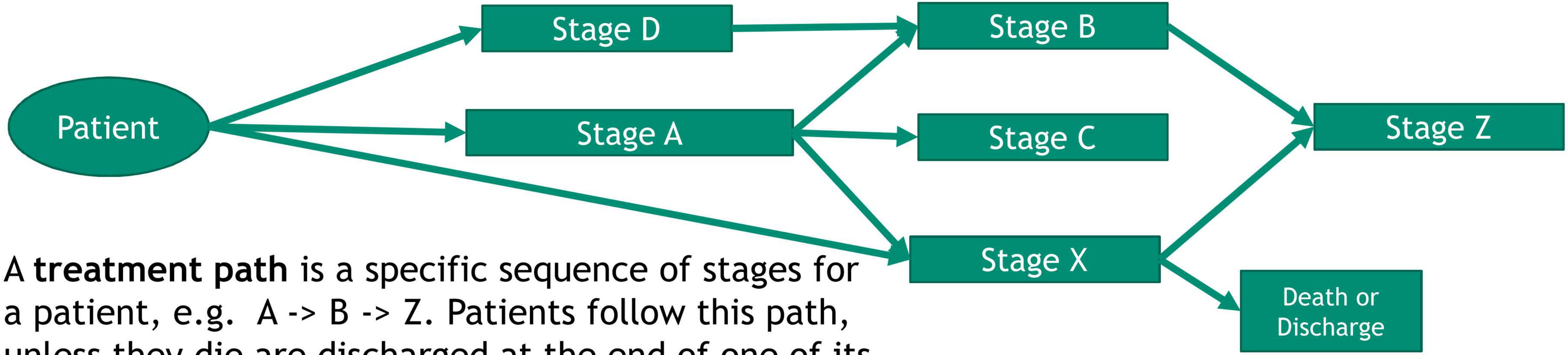


Each stage needs resources:
- *specialists*
- *equipment*
- *resources per patient*
- *resources per practitioner*

Treatment paths and patient fates

Stages model administration of a specific kind of treatment (e.g. ICU, ICU with Ventilation, General)

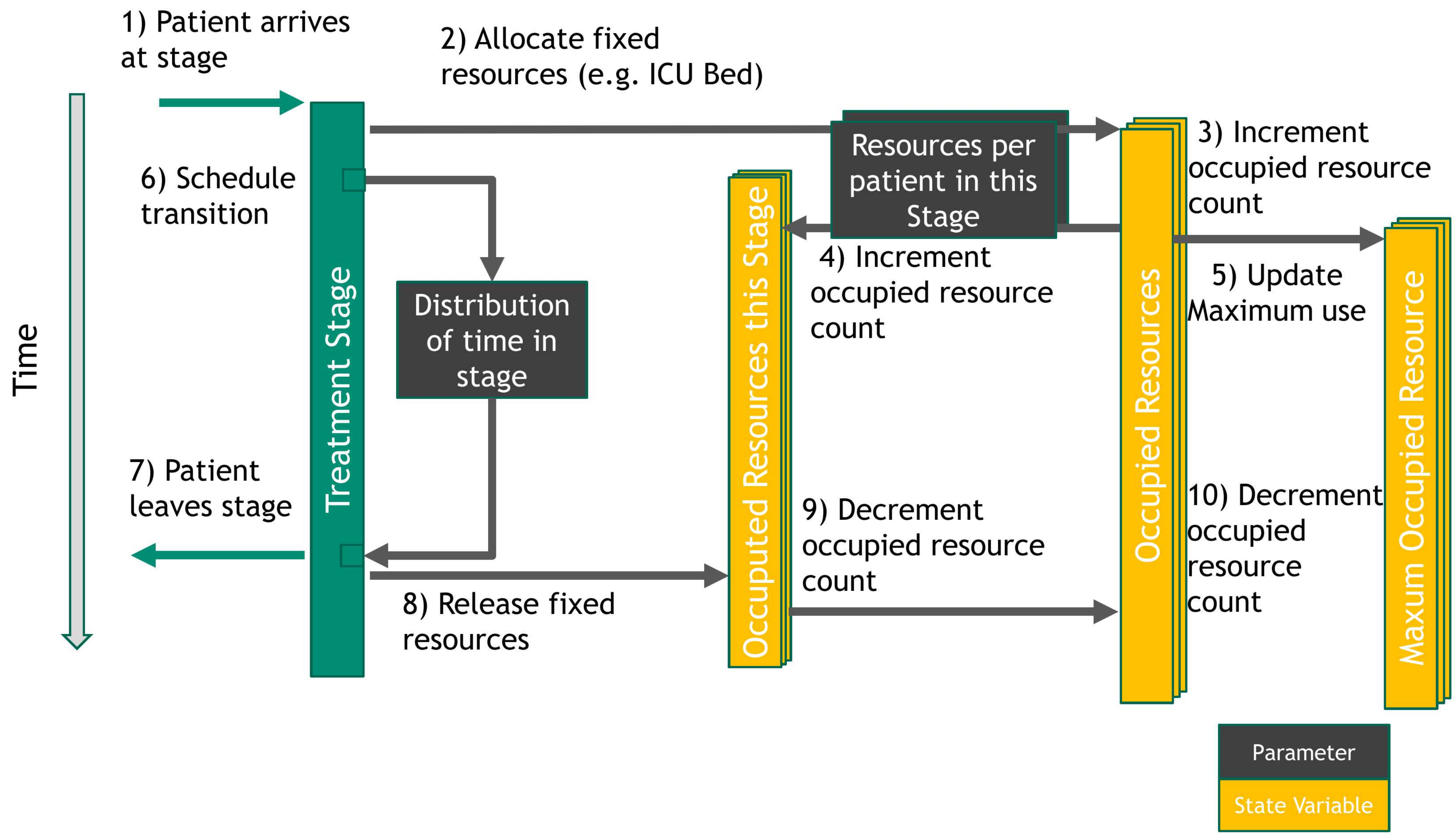
All resource consumption occurs in treatment ***Stages***



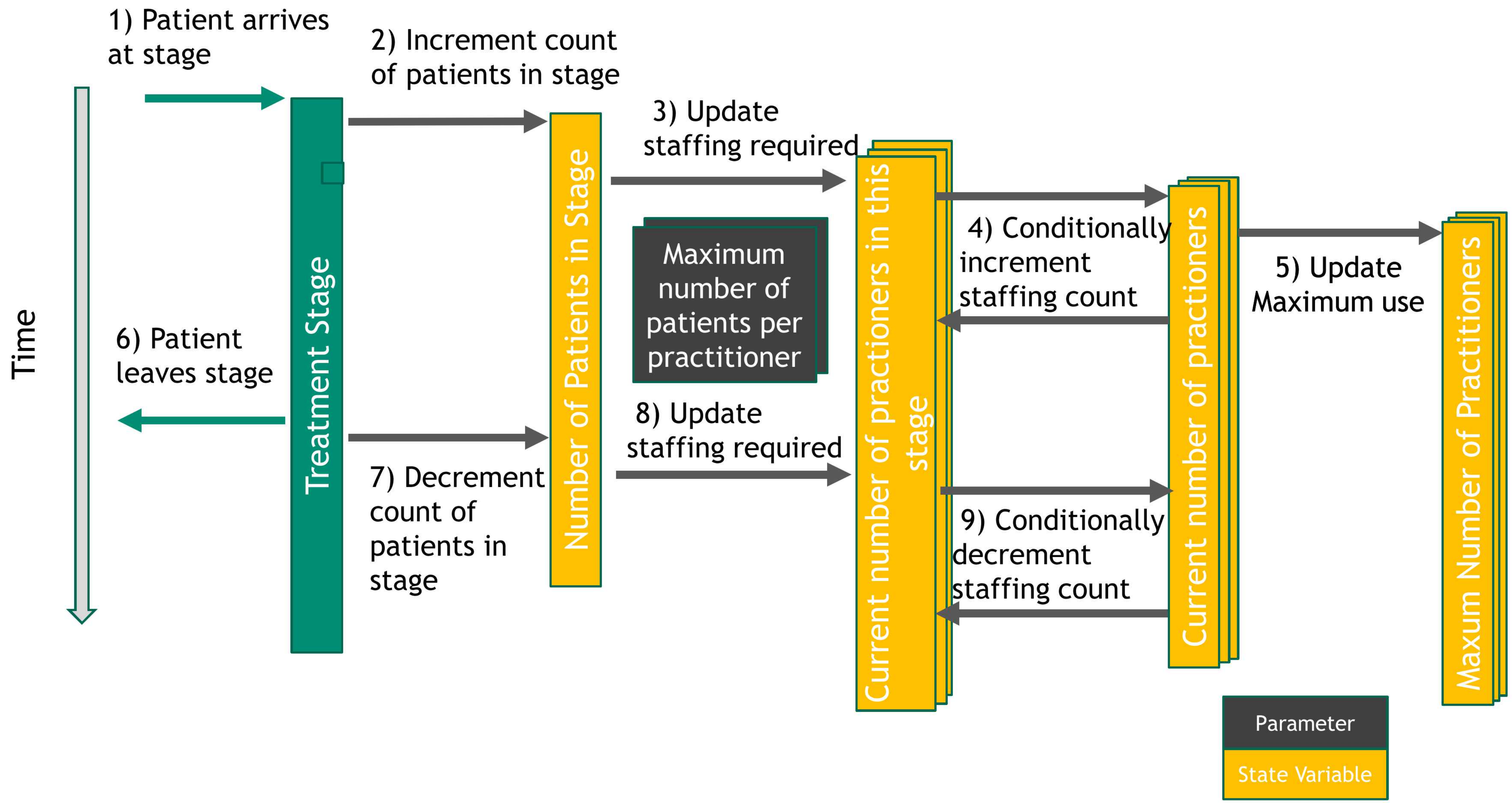
A **treatment path** is a specific sequence of stages for a patient, e.g. A -> B -> Z. Patients follow this path, unless they die are discharged at the end of one of its stages

Fate is a set of rules that connect a patient's demographic characteristics to a set of possible paths with associated probabilities

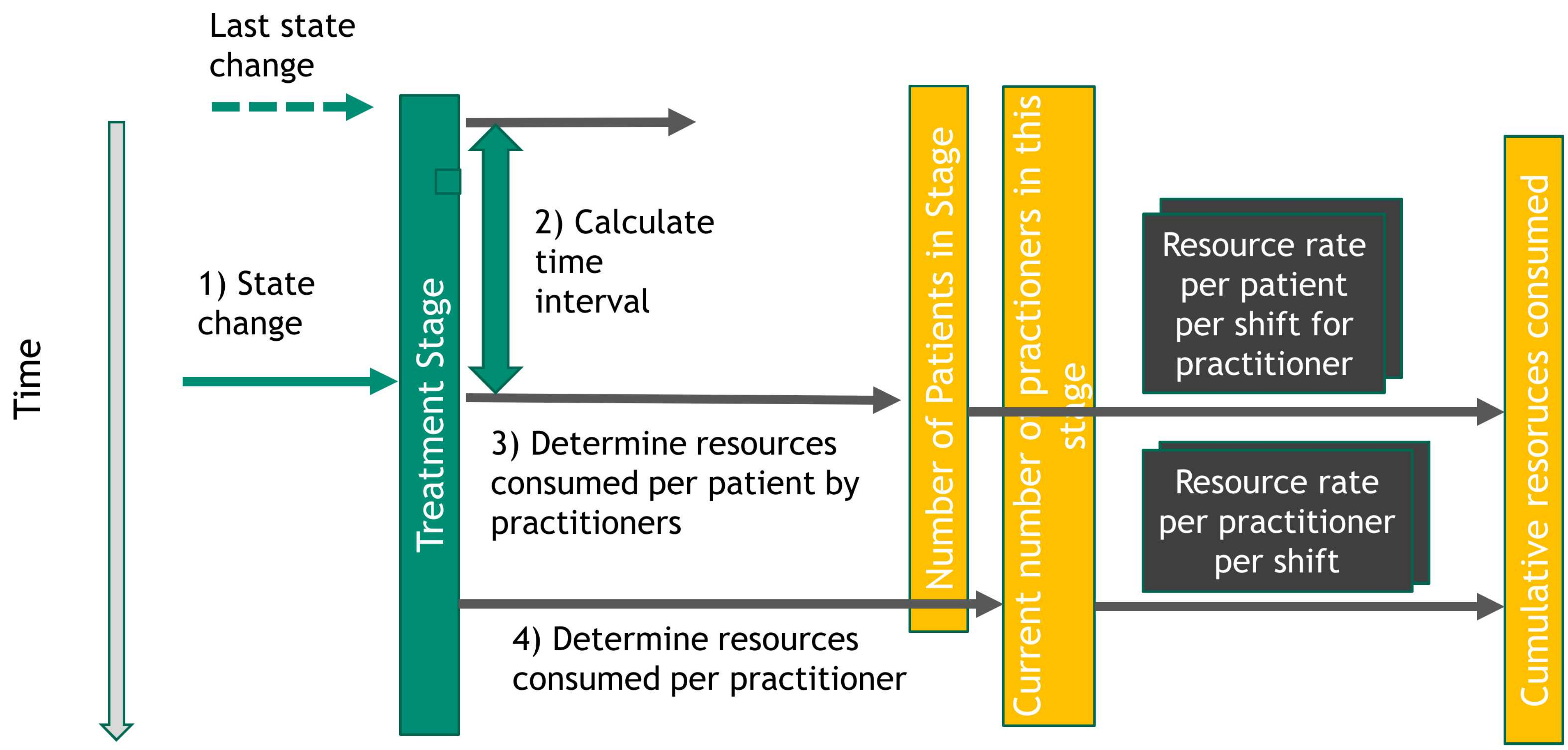
Calculating resource burdens – re-useable resources



Calculating resource burdens – practitioners



Calculating resource burdens – consumables



Parameters summary

Patients are assigned a course of treatment based on demographics. Alternatives are probability-weighted

Fates

Demographic rule
Set of possible trajectories:
- Probability of taking it
- Series of Treatment Stages

Demographics

Age range
Gender
List of Conditions (e.g. “COPD”, “Diabetes”)
Fraction of population

If patients arrive with demographic data that is used. Otherwise their chosen randomly

Treatment stages are defined by their associated resource usage

Treatment Stage

List of resources
Minimum time
Maximum time
Probability of death
Probability of transition to next stage
Types of caregivers required
for each type….
maximum number of patients they can handle
consumable resources per shift
consumable resources per shift per patient

Implementation

Features

- Configurable through input
  - Treatment paths and probabilities
  - Kinds of specialists and resources; requirements at different treatment stages
- Reflects uncertainty about key inputs
- Rapid updates as information and conditions change
- Scalable to state, county, hospital

Application

Outline

Model structure, parameters, and supporting data are common to two distinct analyses

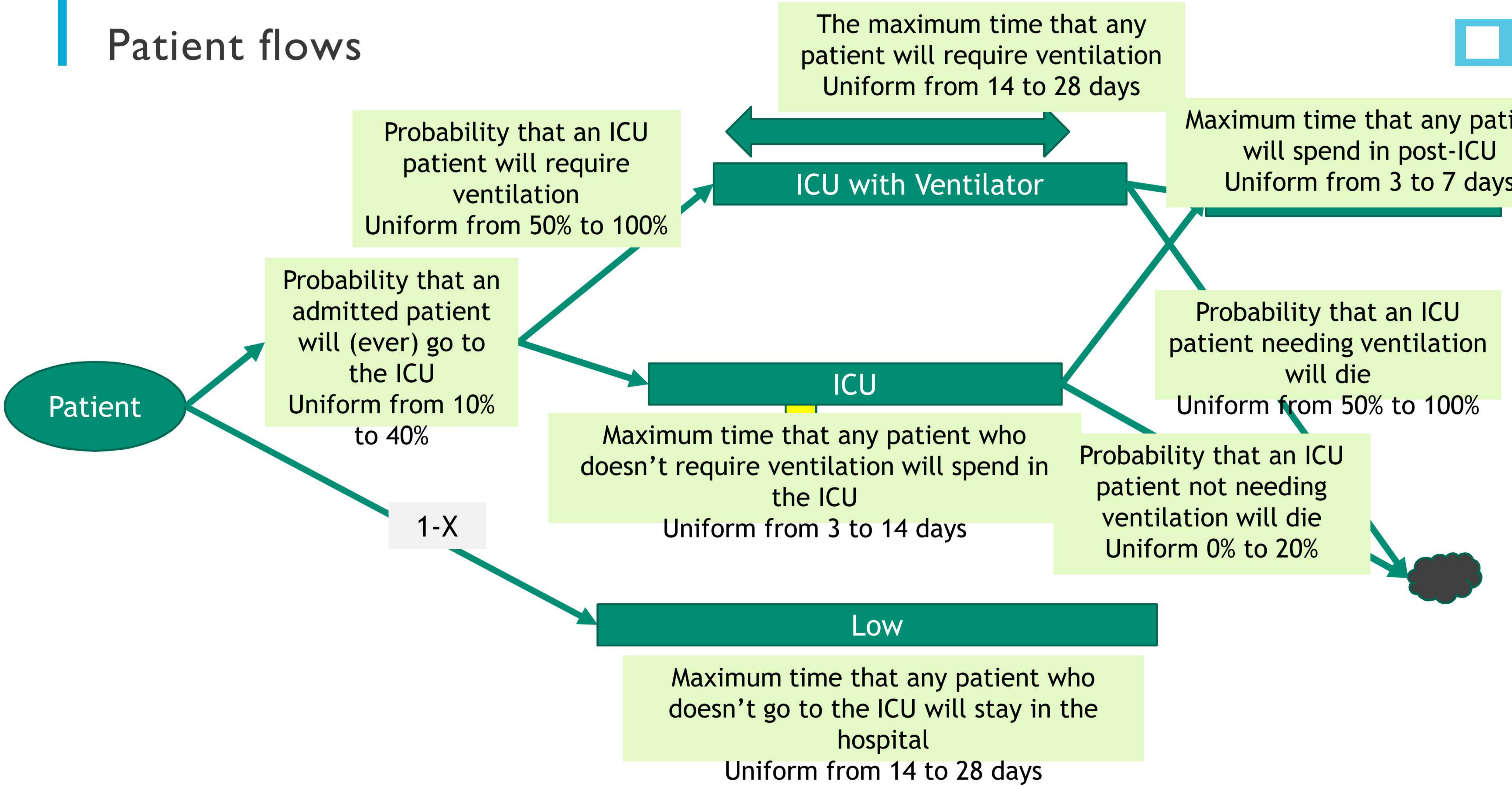
Caveats

First analysis – possible resource needs for New Mexico considering uncertainty in epi forecasts, treatment characteristics, and use rates

- State-level analysis with three epi models
- County-level analysis with EpiGrid results for New Mexico

Second analysis – parametric study of resource demands as a function of patient curve acuity

Patient flows



Roles and resources

Roles:
- Physician
- FloorNurse
- ICUNurse
- RespiratoryTherapist

Committed Resources:
- Ventilator
- MeteredDoseInhaler
- ICUBed
- Bed

Treatments:
- General
- ICU
- SevereICU

Consumable Resources:
- Gown
- N95
- FaceShield
- Gloves
- Sedatives

Notes

- Other resources that scale with ventilation (tubes etc.) are not tracked individually
- Sedatives are a surrogate for other drugs – their cumulative demand is the total number of shifts that a patient is under ventilation

Staffing – Number of patients per practitioner

Role	Context: ICU	Context: General
ICU Nurse	@NP_ICUNurse Uniform 1 to 2	N/A
Doctor	@NP_ICUDoctor Uniform 2 to 10	@NP_GenDoctor Uniform 20 to 50
Nurse	N/A	@NP_GenNurse Uniform 4 to 10
Respiratory Therapist	@NP_RT Uniform 2 to 6	
Lab Tech		
Environmental Services		
Radiology		
ECG Tech		
Healthcare Assistant		

	ICU			
Units used per shift				
Practitioner	Gowns	N95 Mask	Gloves	Face Shield
Floor Nurse				
ICU Nurse	@NGown_ICUNurse 2-4	@NMask_ICUNurse 1-4	@NGloves_ICUNurse 4-12	@NShield_ICUNurse 1-4
Doctor	@NGown_ICUDoc 1-2	1	@NGloves_ICUDoc 1-12	1
RT	@NGown_ICURT 1-2	1	@NGloves_ICURT 6-12	1

	General			
Units used per shift				
Practitioner	Gowns	N95 Mask	Gloves	Face Shield
Floor Nurse	@NGown_GenNurse 2-3	@NMask_GenNurse 1-3	@Ngloves_GenNurse 3-12	1
ICU Nurse				
Doctor	@NGown_GenDoc 1-2	1	@NGloves_GenDoc 1-12	1
RT				

References – treatment paths and outcomes

Guan WJ, Ni ZY, Hu Y, et al; China Medical Treatment Expert Group for Covid-19. Clinical characteristics of coronavirus disease 2019 in China. *N Engl J Med*. doi:10.1056/NEJMoa2002032

Wang D, Hu B, Hu C, et al. Clinical Characteristics of 138 Hospitalized Patients With 2019 Novel Coronavirus–Infected Pneumonia in Wuhan, China. *JAMA*. 2020;323(11):1061–1069. doi:10.1001/jama.2020.1585

Clinical course and outcomes of critically ill patients with SARS-CoV-2 pneumonia in Wuhan, China: a single-centered, retrospective, observational study. Yang X, Yu Y, Xu J, Shu H, Xia J, Liu H, Wu Y, Zhang L, Yu Z, Fang M, Yu T, Wang Y, Pan S, Zou X, Yuan S, Shang Y.

Severe Outcomes Among Patients with Coronavirus Disease 2019 (COVID-19) — United States, February 12–March 16, 2020 - CDC

Clinical Characteristics of Coronavirus Disease 2019 in China .Wei-jie Guan, Ph.D., Zheng-yi Ni, M.D., et al. doi: 10.1056/NEJMoa2002032; 10.1056/NEJMoa2002032; New England Journal of Medicine; Massachusetts Medical Society; 0028-4793; UR - https://doi.org/10.1056/NEJMoa2002032;2020/04/04

Preliminary Analysis of case data from Canada and New Mexico

References – usage rates

Planning estimates provided by a local New Mexico health service

Preliminary Analysis of hospital usage and staffing reports provided by NMHA

CDC guidance cited in: Potential Demand for Respirators and Surgical Masks During a Hypothetical Influenza Pandemic in the United States; Cristina Carias,[1,2] Gabriel Rainisch,[3] Manjunath Shankar,[3] Bishwa B. Adhikari,[3] David L. Swerdlow,[1,4] William A. Bower,[5] Satish K. Pillai,[3] Martin I. Meltzer,[3] and Lisa M. Koonin

Analyses

Caveats

Model Framework

- Practitioners have fixed roles and are dedicated to specific stages – possible overestimation of personnel

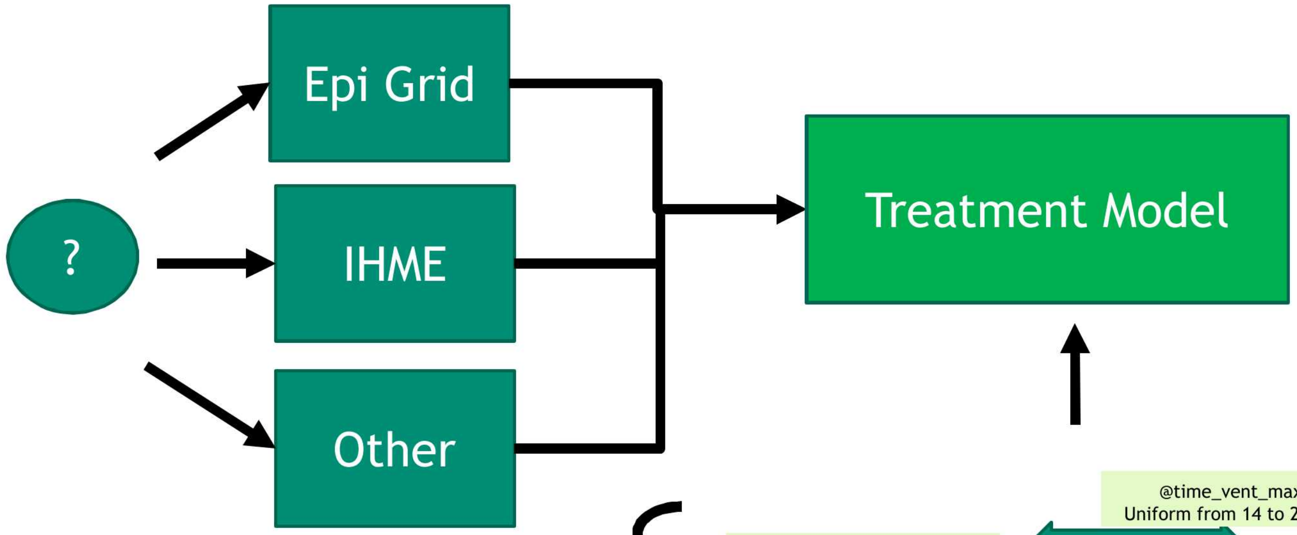
Model Implementation

- The code is simple and provides correct answer to a set of test cases; unit tests, documentation, and review are forthcoming

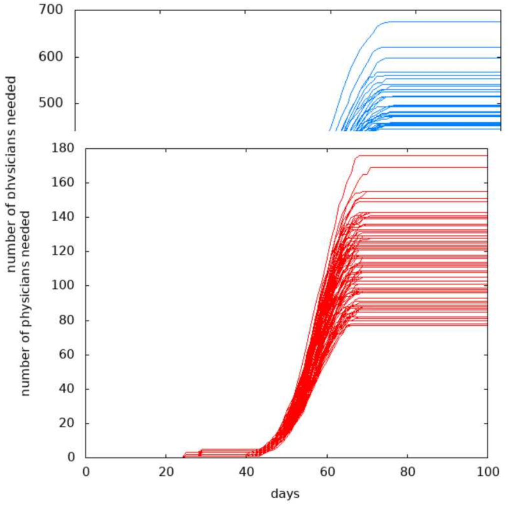
Configuration/Parameters

- Resource requirements from background medical services are not included
- Some categories of workers (e.g. Environmental Services) were not included
- PPE consumption rates in this context are not well characterized. Input reflects planning and recent practice
- Patient feeds from the epi models do not come with demographic characteristics; Treatment pathway probabilities are therefore not conditional on age, pre-existing conditions, etc.
- Relationship between inherent stochasticity (e.g. running model replications with the same parameters) vs. changing governing parameter (uncertainty) not yet characterized
- Initial results suggest output is dominated by scale of patient stream from epi model, but parameter uncertainty is also significant (e.g. the ratio of standard deviation to the mean is 0.3-0.4 for many response quantities, which results in wide uncertainty predictions). Properly accounting for epi scenario uncertainty vs. parameter uncertainty will be case-specific and is an important aspect of these studies.

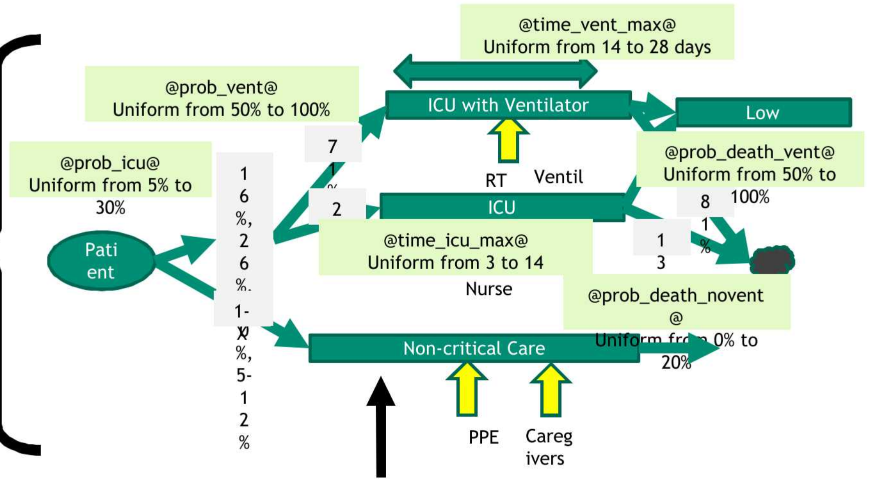
Analysis Plan – Possible resource needs



Uncertainty analysis



Possible treatment paths, durations, outcomes



Resources required by specific practitioners and contexts

Resources needed to treat patient load

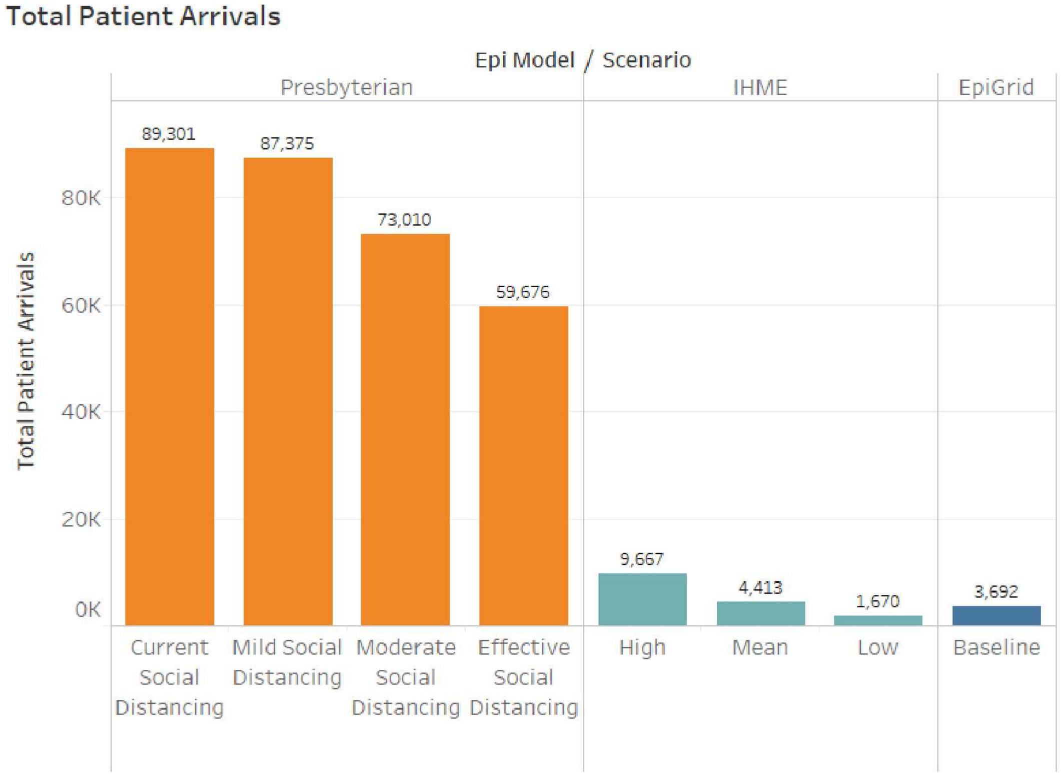
- Practitioners by specialty
- PPE of different kinds
- Other resources per NMHA needs

Analysis 1: Inputs

Goal: How does using a different epi input effect resource planning?

Three different epi models (each with different scenarios) are available for New Mexico

All models and scenarios have very different projections for total patient arrivals



Analysis 1: Results

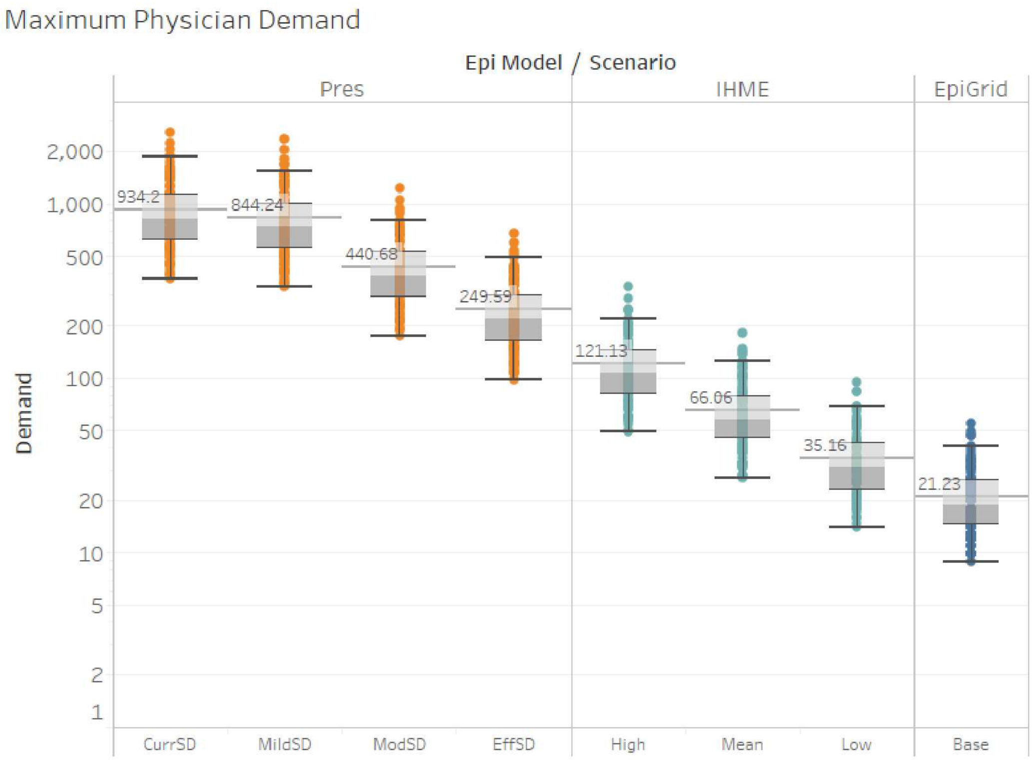
Results are presented in three ways:

- Dot plots that show range of maximum value for resource needs across all scenarios
- Table that shows mean values across all scenarios
- Time series with mean and 5^{th}-95^{th} percentiles

Analysis I: Results

Given the variation in possible patient arrivals, there is a wide range of resource demands as output from our model

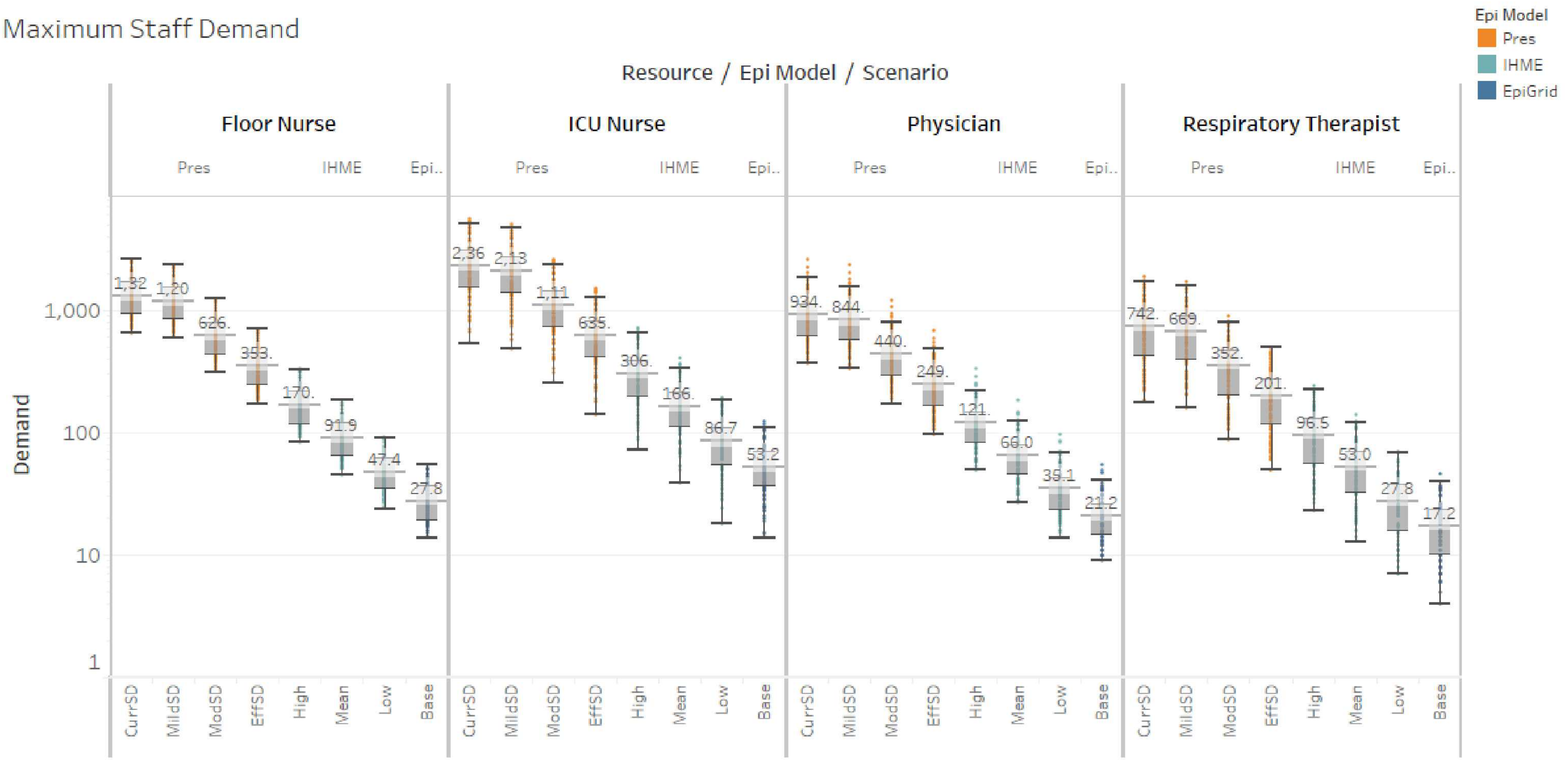
Example for Physician demand:



Ranges within a scenario dictated by uncertainties in parameters (e.g., probability the patient goes into the ICU, needs a ventilator, or length of stay)

Analysis 1: Results

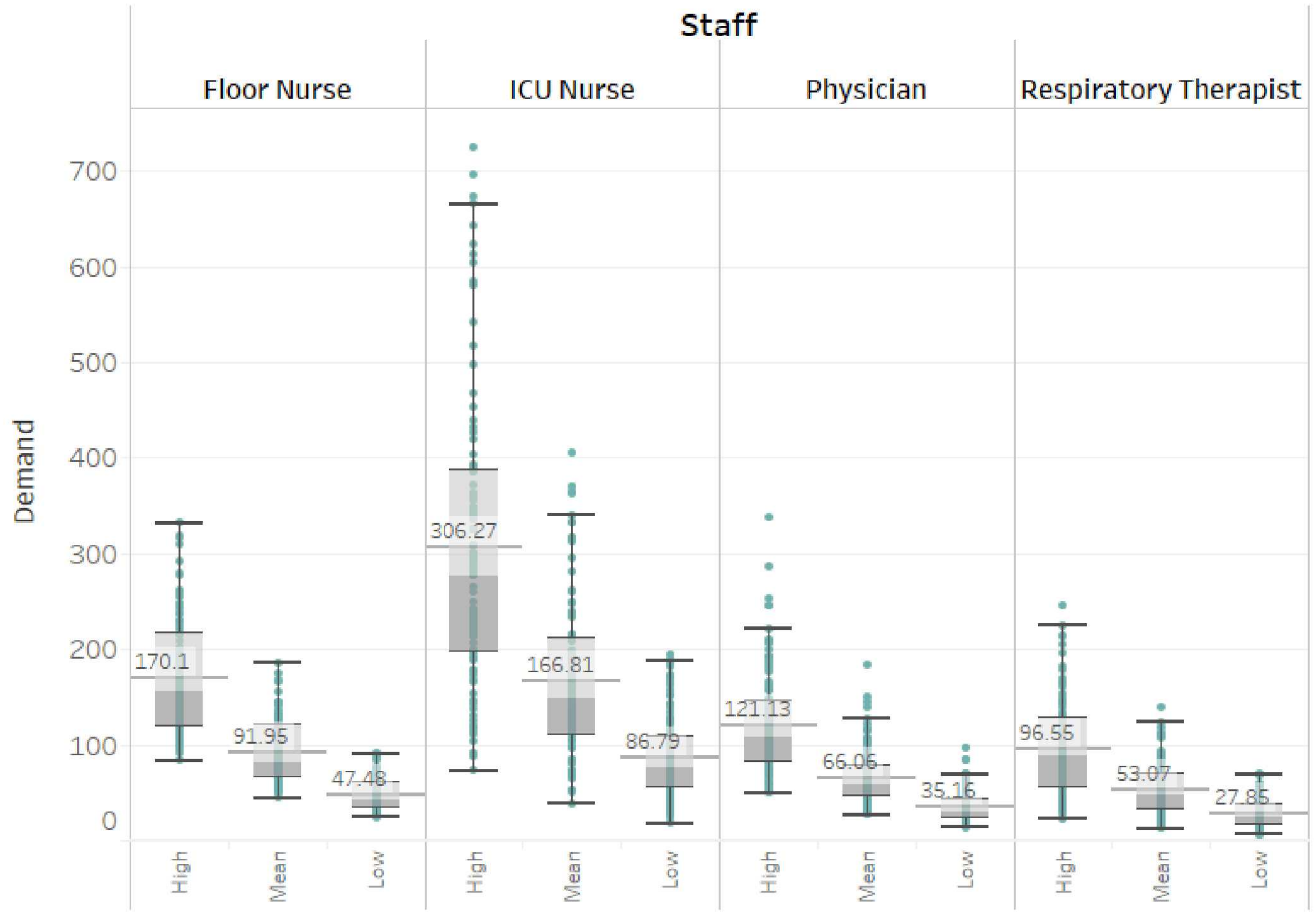
Compare staff demand across all epi models and scenarios



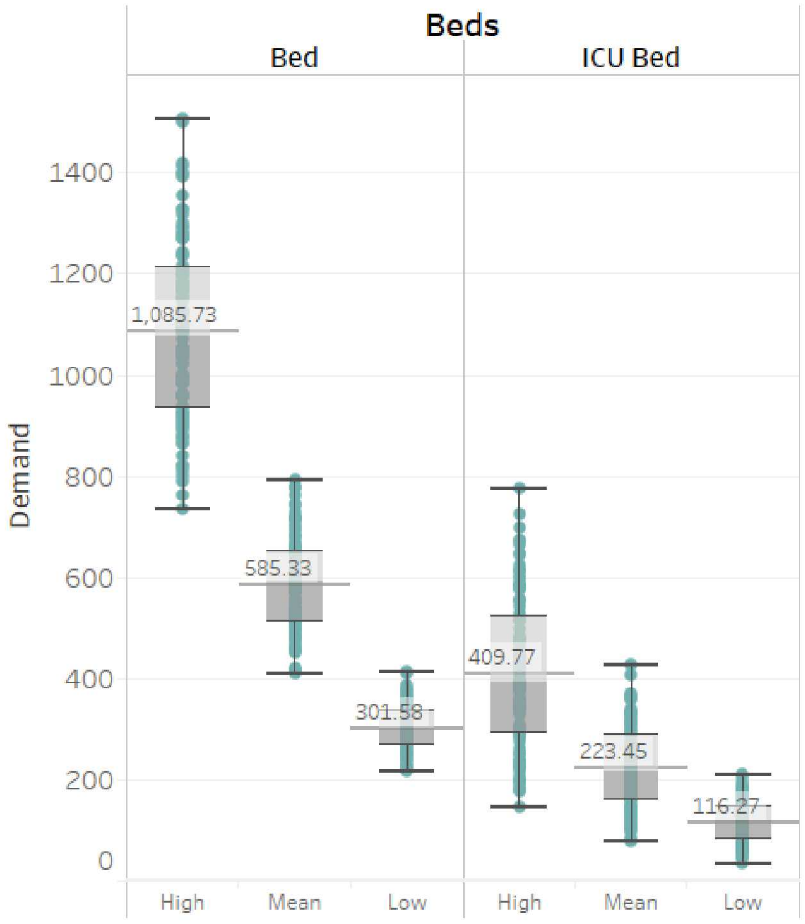
Analysis 1: Results For IHME Patient Arrivals

Choose a subset of epi models to see all resource needs (slide 1 of 2)

Maximum Staff Demand for IHME Model



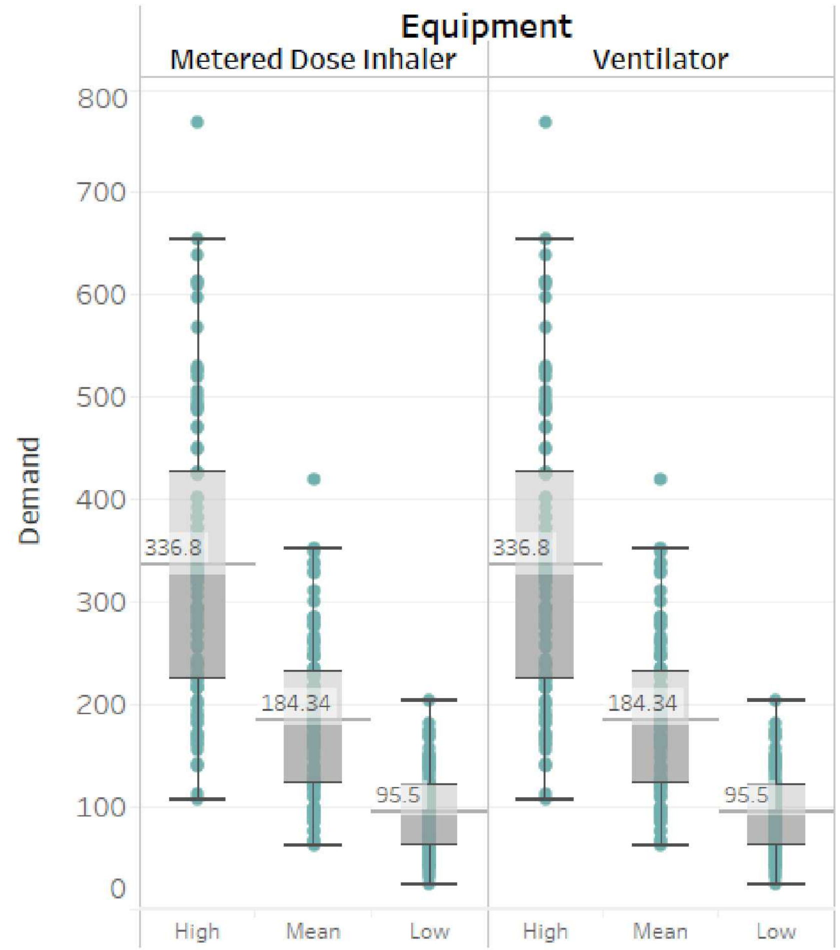
Maximum Bed Demand for IHME Model



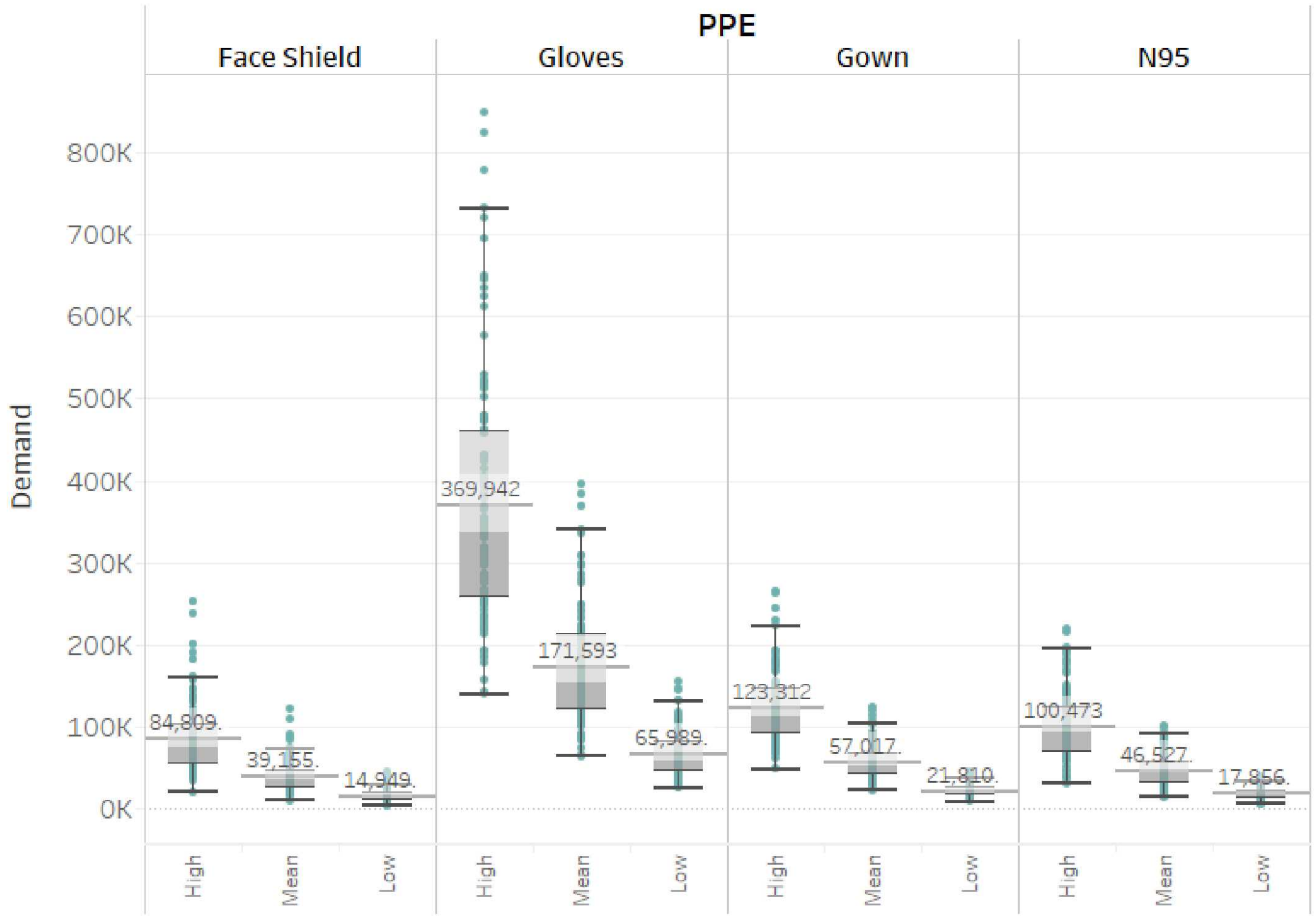
Analysis 1: Results For IHME Patient Arrivals

Choose a subset of epi models to see all resource needs (slide 2 of 2)

Maximum Equipment Demand for IHME Model

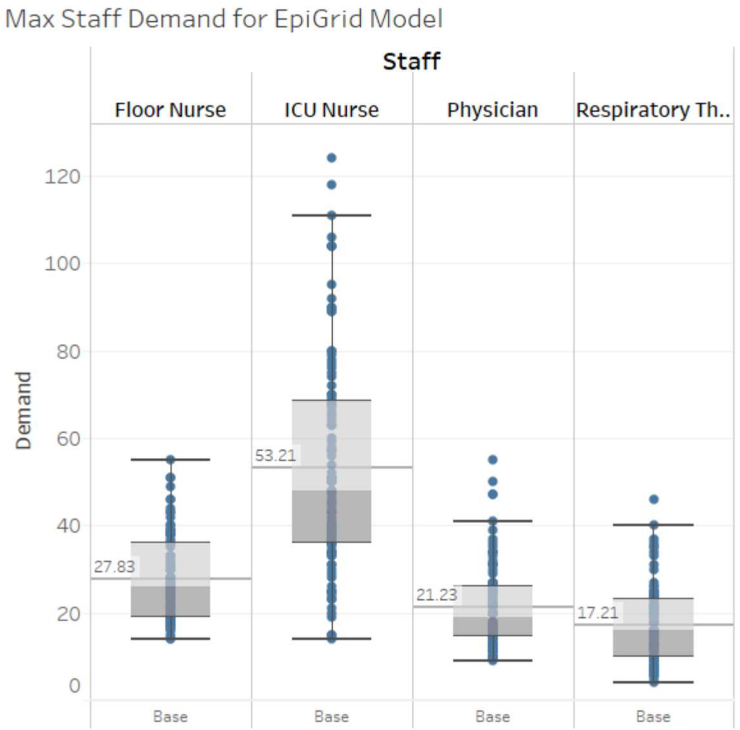


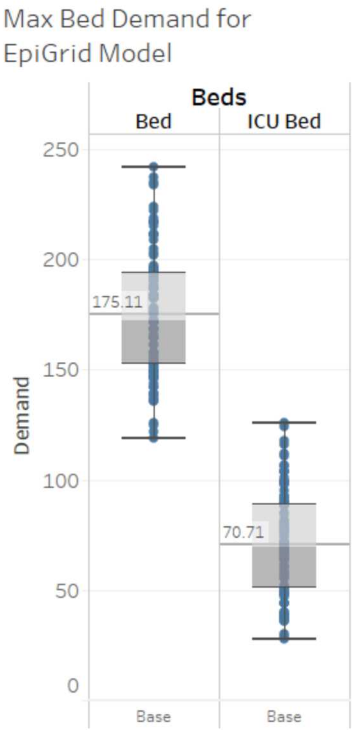
Cumulative PPE Demand for IHME Model

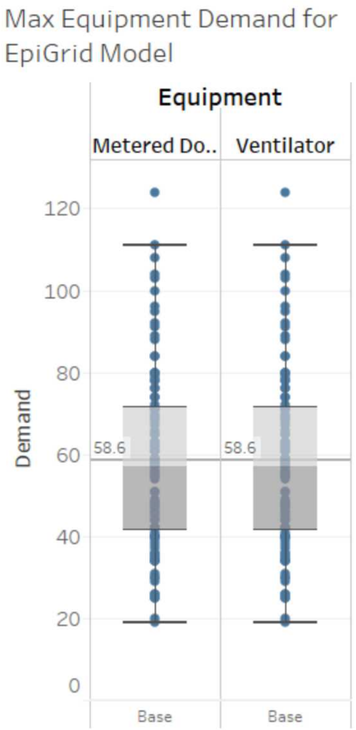


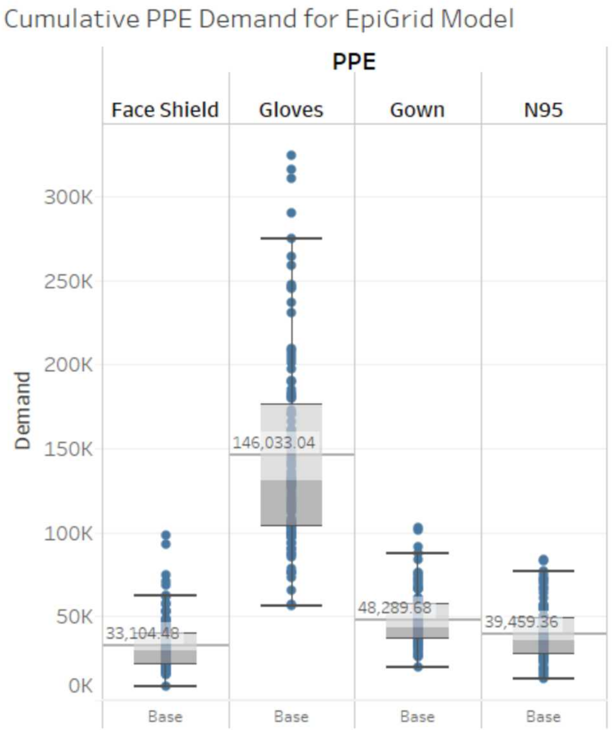
Analysis 1: Results For EpiGrid Patient Arrivals

All resource needs for only the EpiGrid model





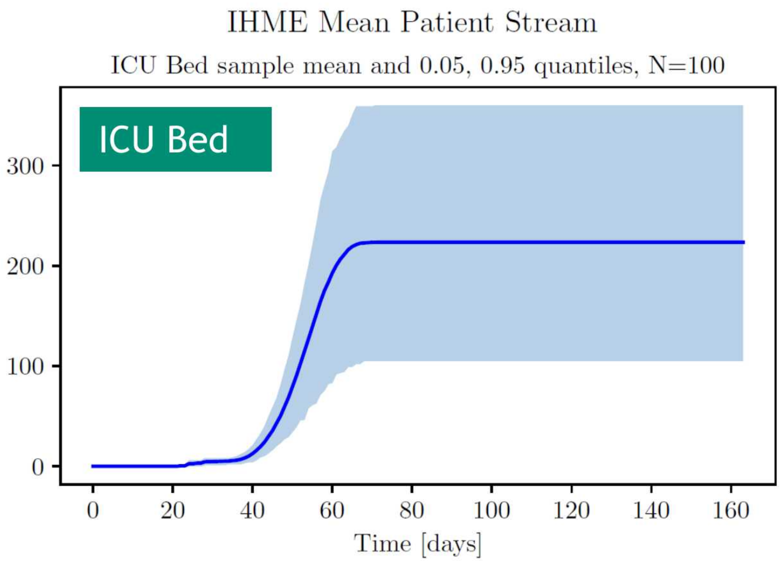


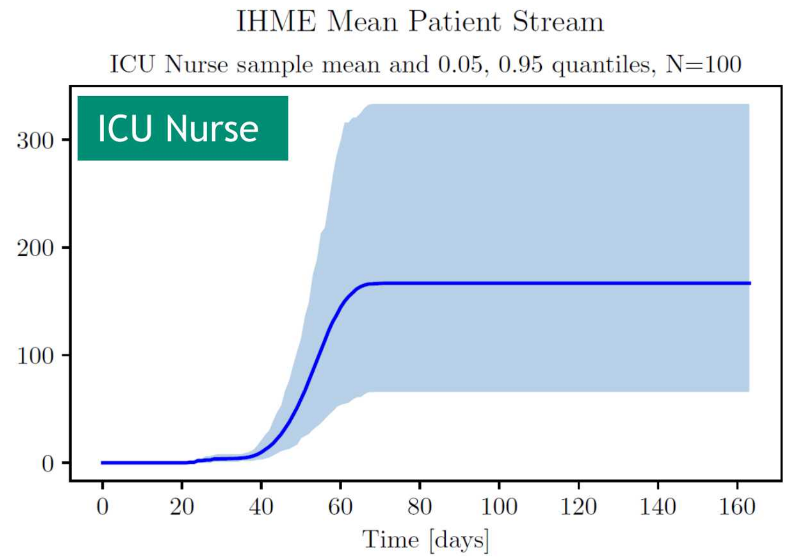


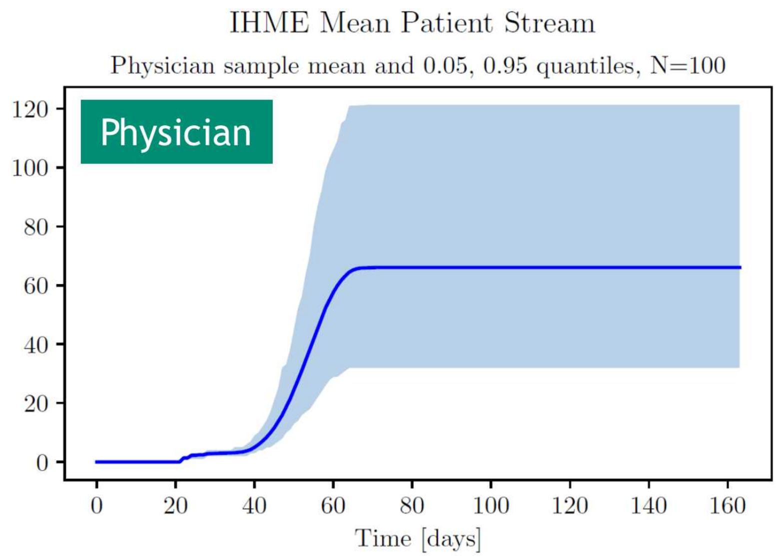
Analysis 1: Results, Summary Table

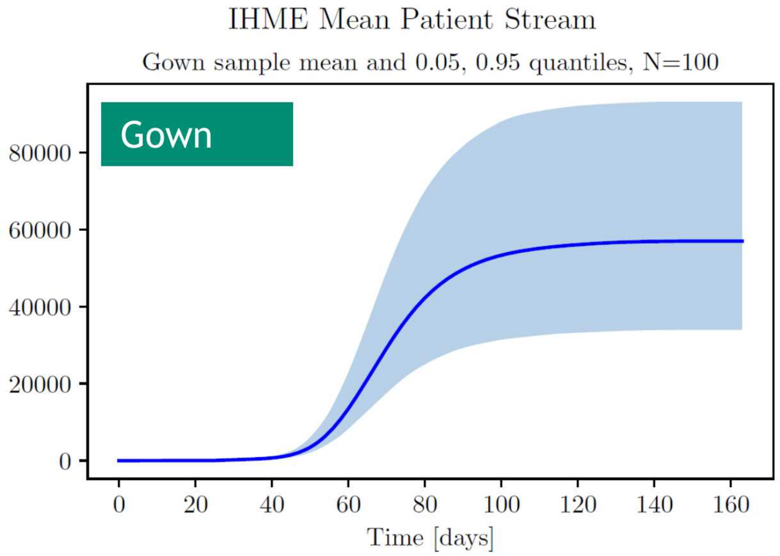
				Staff				Beds		Equipment		PPE			
Epi Model	**Scenario**	**Patient Arrivals**	**Statistic**	**Floor Nurse**	**ICU Nurse**	**Physician**	**Respiratory Therapist**	**Bed**	**ICU Bed**	**Metered Dose Inhaler**	**Ventilator**	**Gown**	**N95**	**Face Shield**	**Gloves**
EpiGrid	Baseline	3692	Mean	28	53	21	17	175	71	59	59	48290	39459	33104	146033
			Std. Dev.	10	25	10	9	28	24	22	22	16490	16061	16079	59208
Local Health Serice	Current Social Distance	89301	Mean	1327	2365	934	742	8484	3166	2592	2592	1131010	921016	777526	3382158
			Std. Dev.	474	1196	437	396	1410	1154	1082	1082	405547	387836	391231	1417676
	Mild Social Distance	87375	Mean	1201	2137	844	670	7681	2862	2345	2345	1106999	901700	761195	3310546
			Std. Dev.	430	1078	394	355	1281	1037	978	978	396456	380377	383989	1388278
	Moderate Social Distance	73010	Mean	627	1118	441	352	4004	1498	1232	1232	925827	754096	636283	2770594
			Std. Dev.	226	559	206	185	680	541	509	509	330577	316688	318896	1162189
	Effective Social Distance	59676	Mean	354	636	250	201	2260	850	703	703	757678	617061	520709	2267789
			Std. Dev.	127	321	116	106	387	307	291	291	270134	259059	260661	949049
IHME	High	9667	Mean	170	306	121	97	1086	410	337	337	123313	100473	84810	369943
			Std. Dev.	60	154	56	51	179	148	140	140	43565	42012	42331	154683
	Mean	4413	Mean	92	167	66	53	585	223	184	184	57017	46527	39155	171593
			Std. Dev.	32	83	30	28	92	81	75	75	20107	19399	19547	71825
	Low	1670	Mean	47	87	35	28	302	116	96	96	21811	17856	14950	65989
			Std. Dev.	16	43	16	15	45	42	39	39	7637	7402	7353	27649

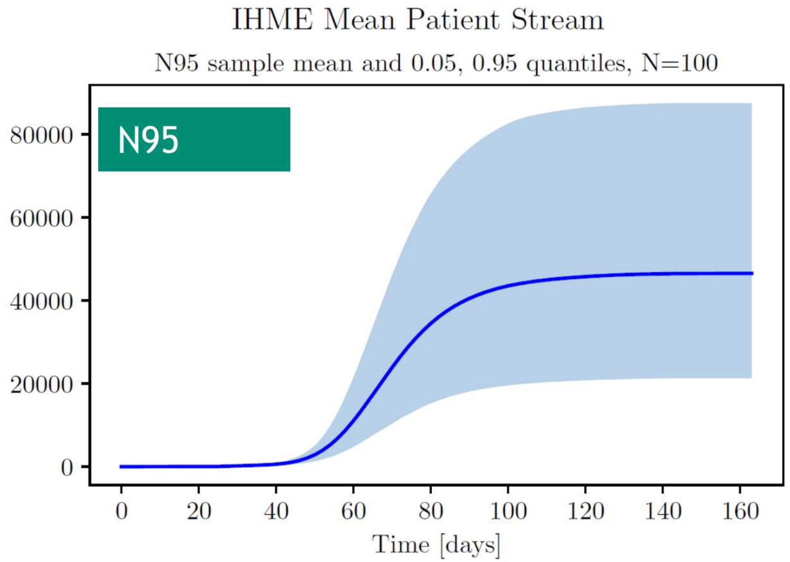
Analysis 1: Results, Time Series for IHME Mean Patient Stream



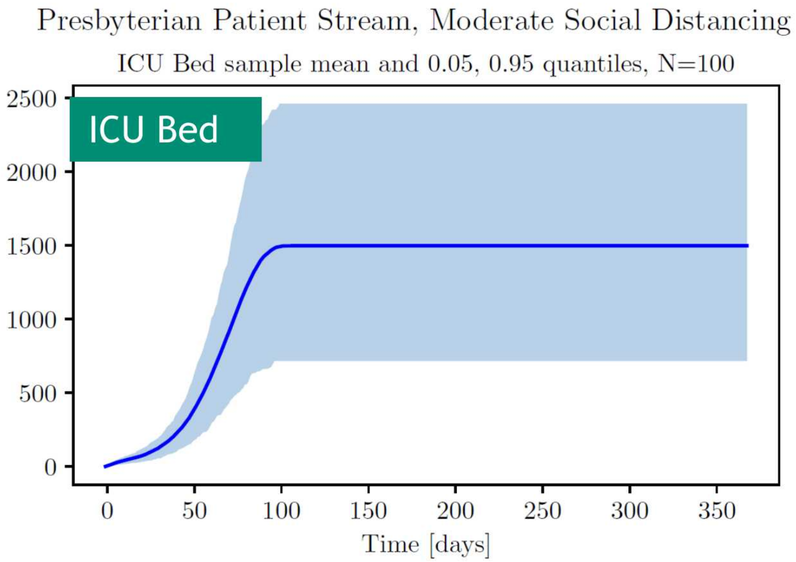


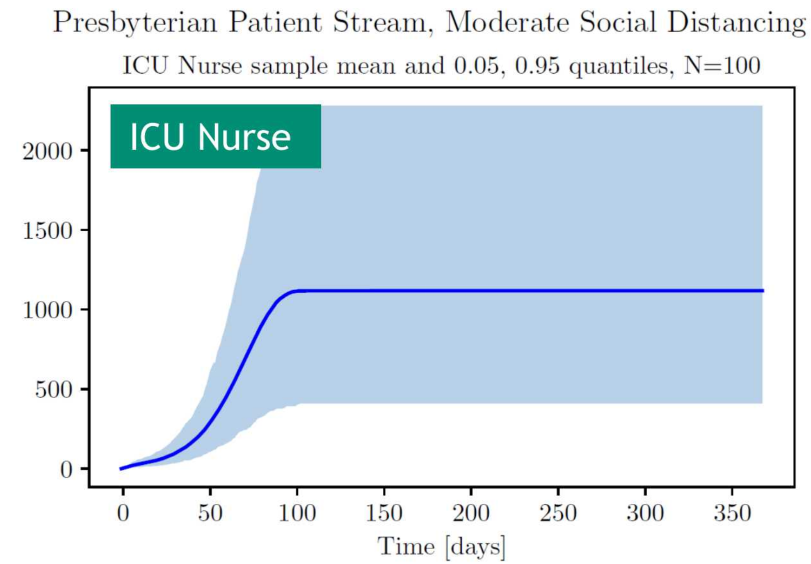


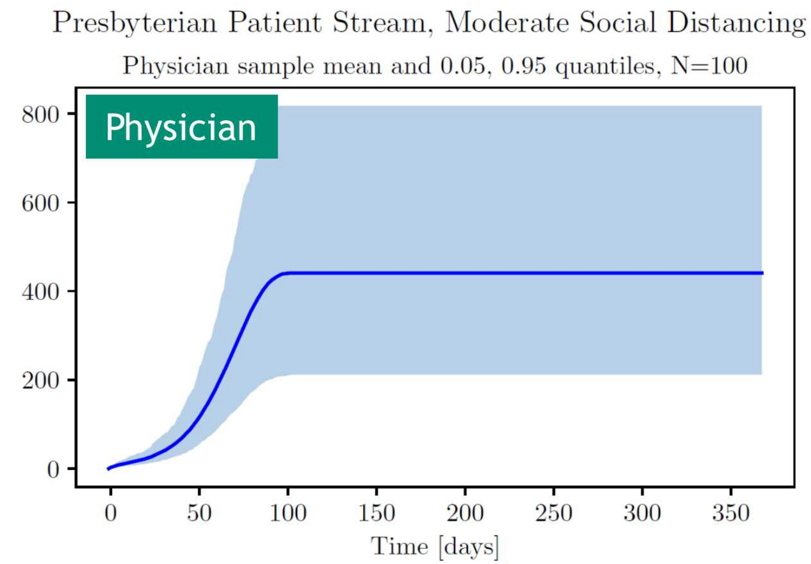


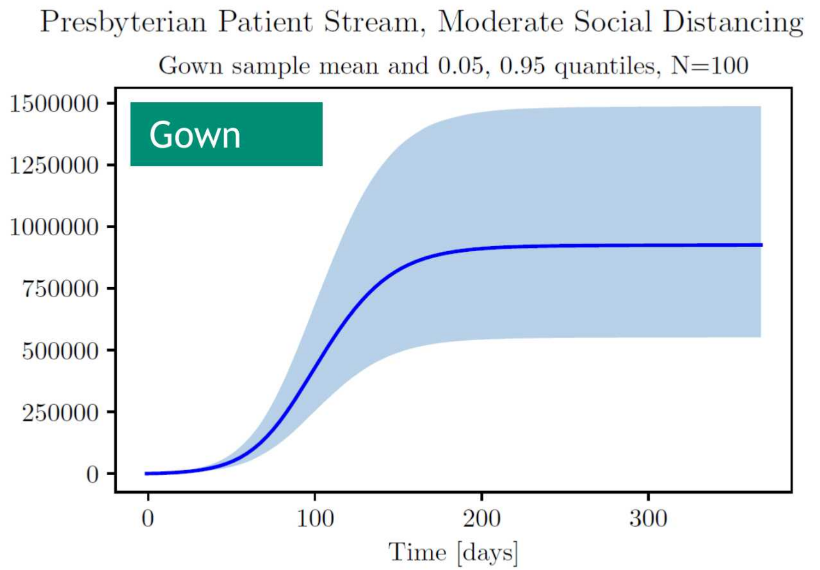


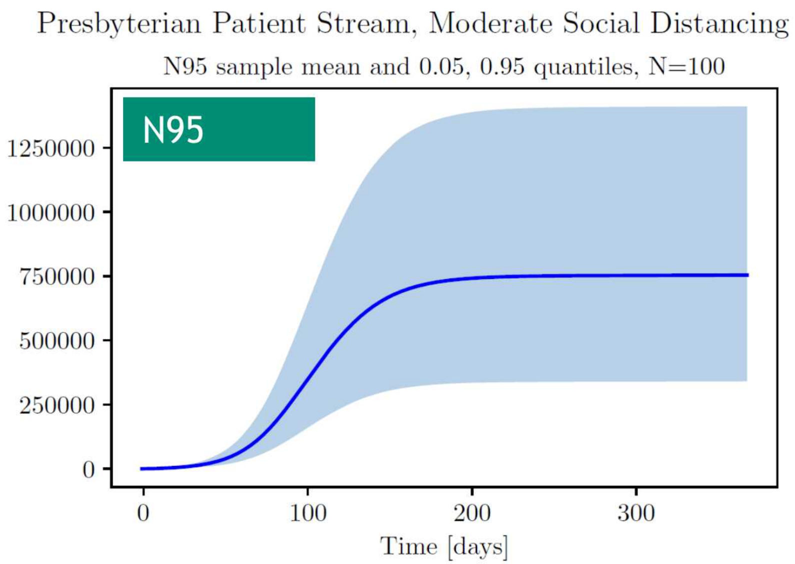
Analysis 1: Results, Time Series for Patient Stream Forecast from a Local Health Service Model



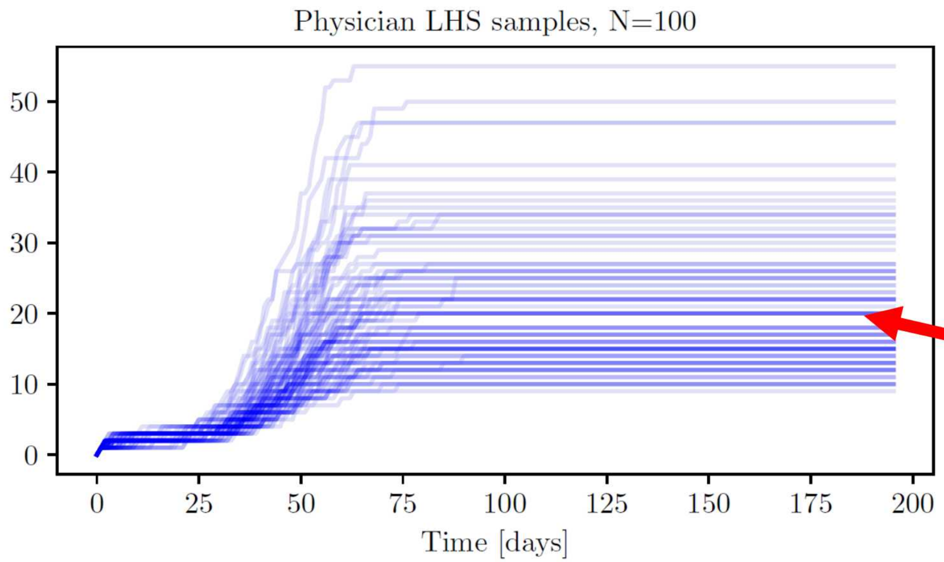




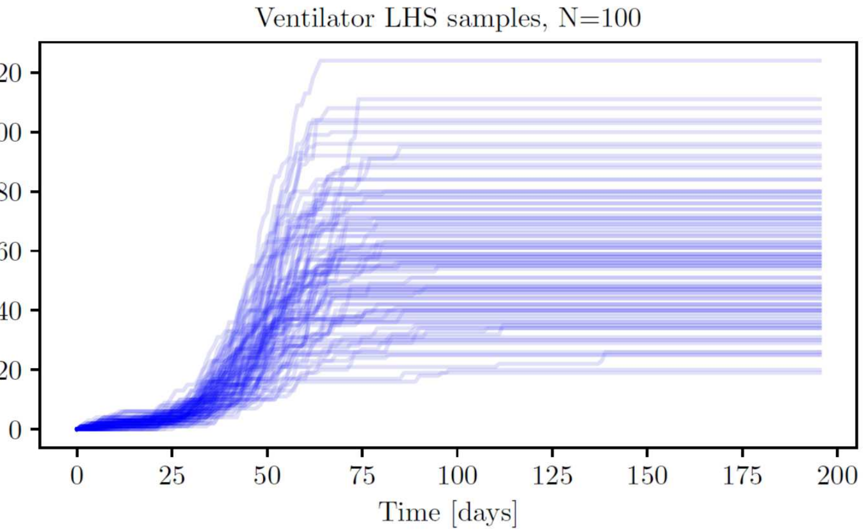


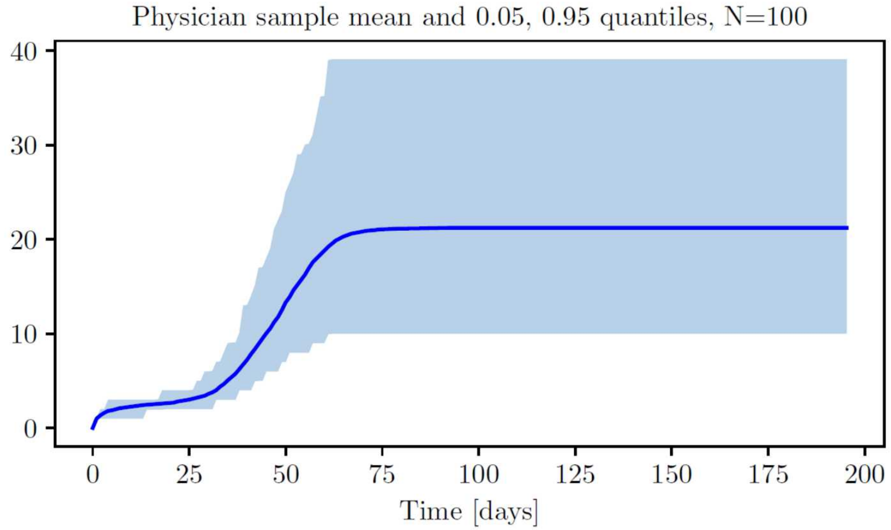


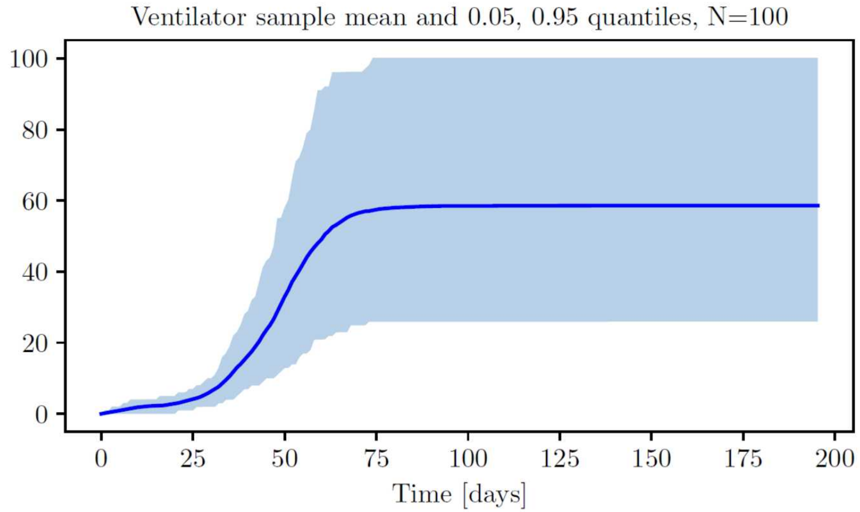
Analysis 1: Results, Time Series for EpiGrid Patient Stream



Many samples skewed toward the low end



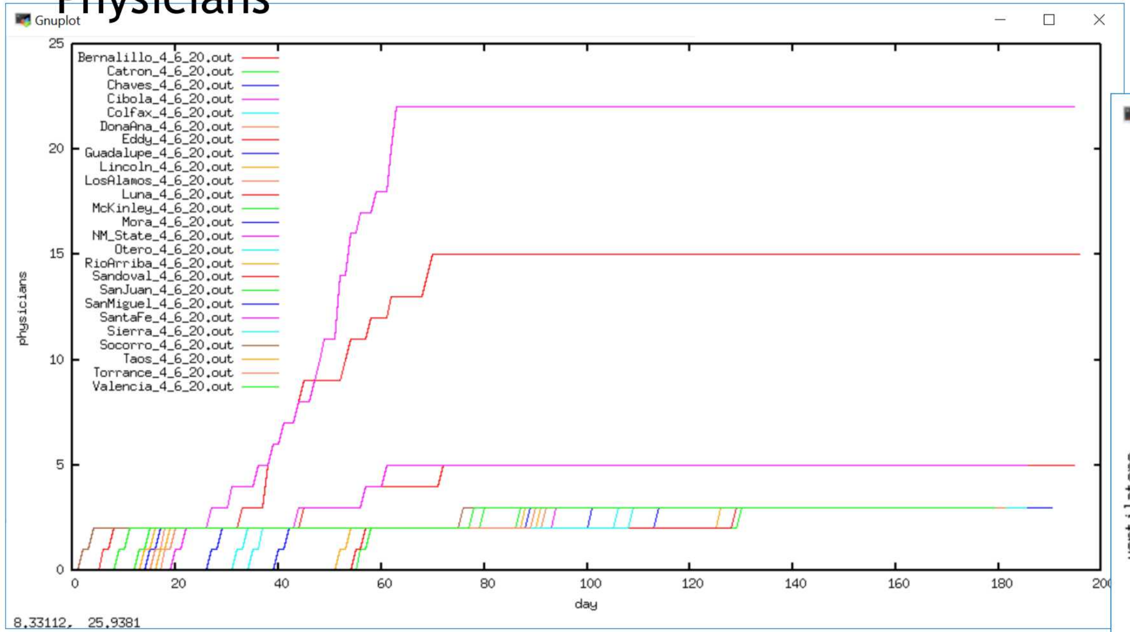




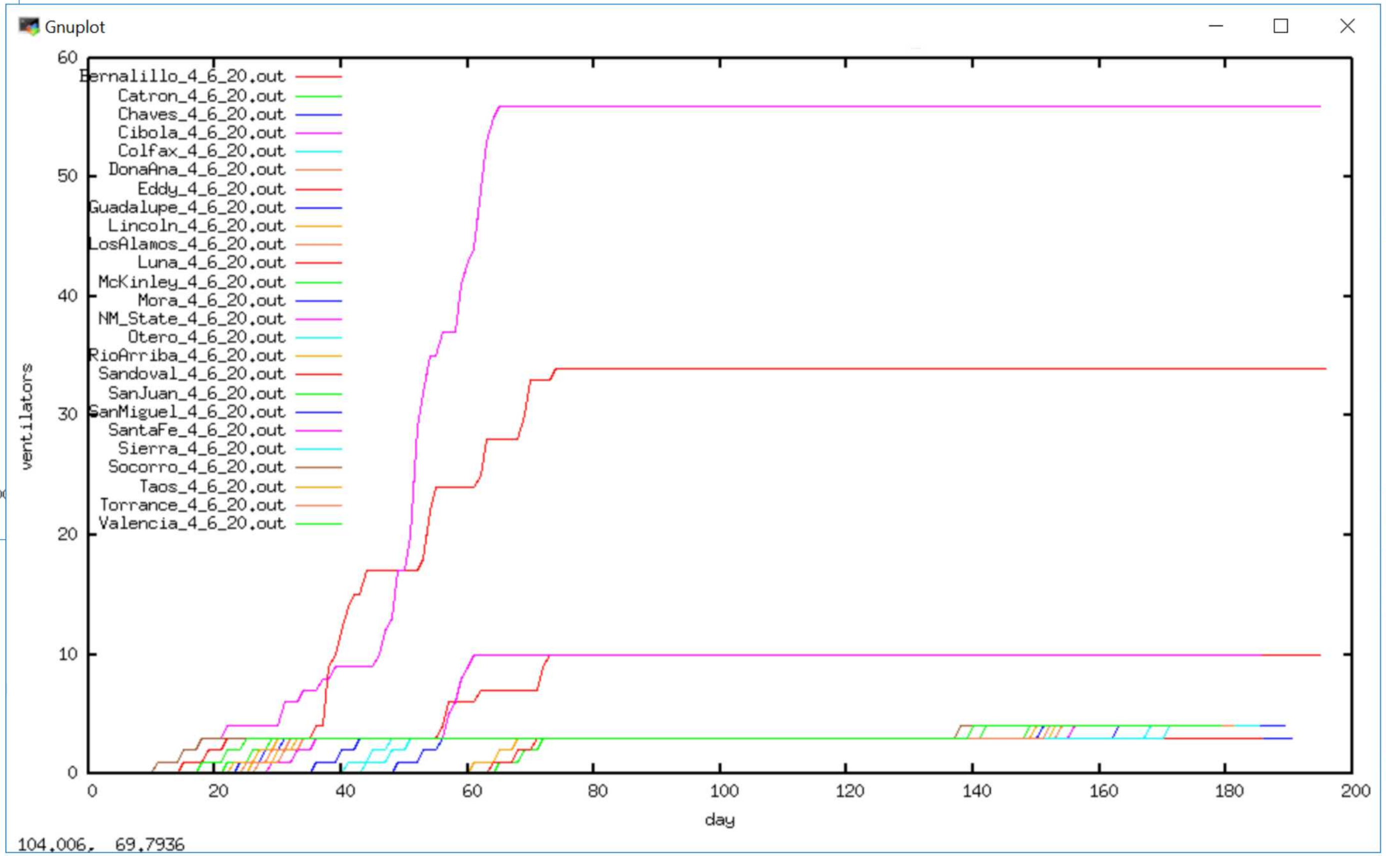
Analysis 1: County-Level

Using EpiGrid county-level projections for New Mexico

Physicians



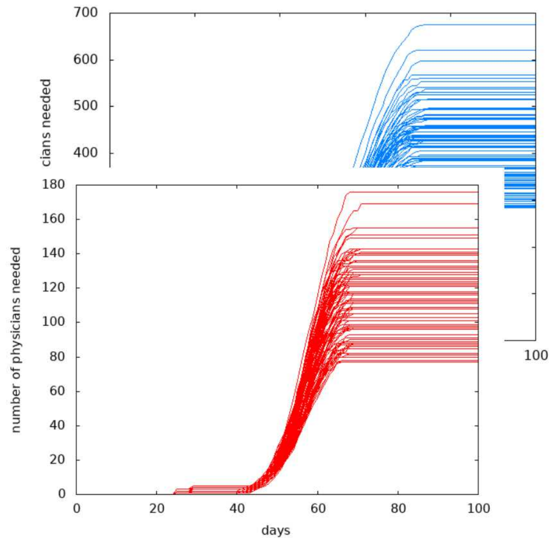
Ventilators



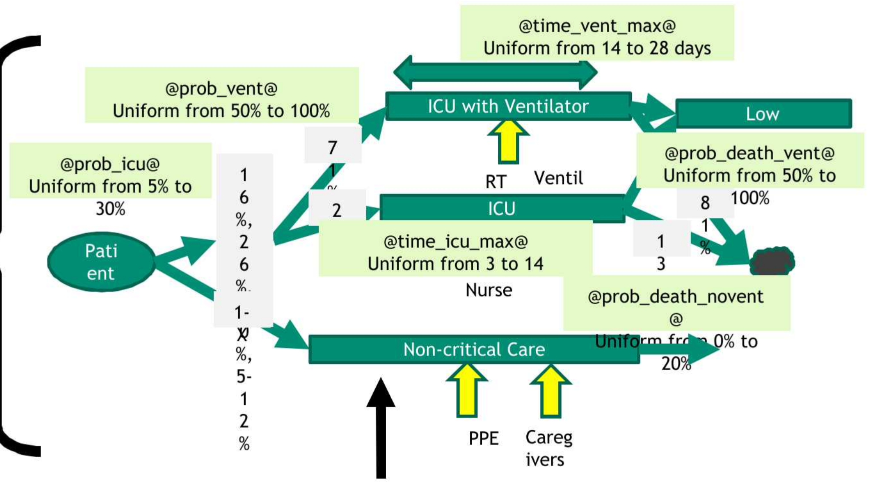
Analysis Plan – Policy scanning

Patient Stream → Treatment Model

Uncertainty analysis



Possible treatment paths, durations, outcomes



Resources required by specific practitioners and contexts

Resources needed to treat patient load
- **Practitioners by specialty**
- **PPE of different kinds**
- **Other resources per NMHA needs**

Bending the Curve

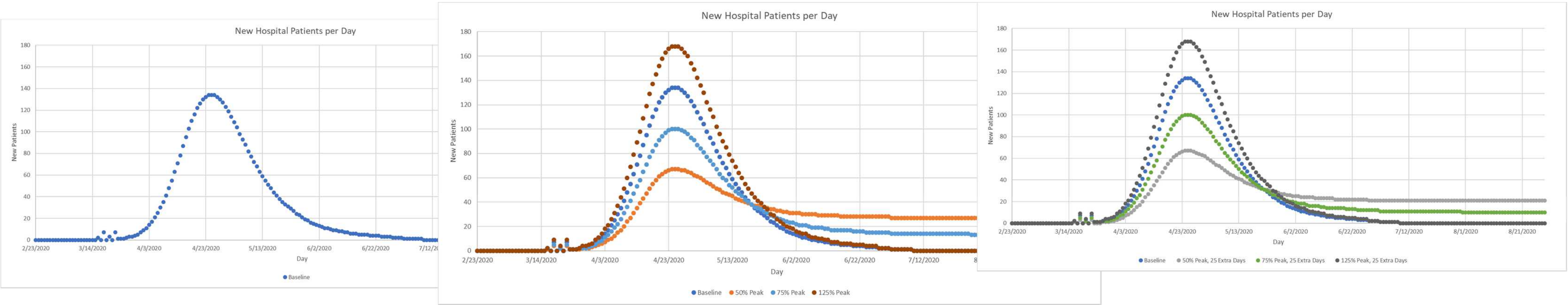
A process developed to synthetically modify patient curves to simulate changes to epidemiological results.

These do not represent epidemiological results of policies (social distancing, stay-at-home, etc.) but rather are notional examples of what the effects of "bending the curve" is on resource usage.

Patient curve modification can address multiple goals:

- Reducing peak but maintaining the same number of patients over time
- Extending the time horizon
- Matching the curve shape to a specific patient count

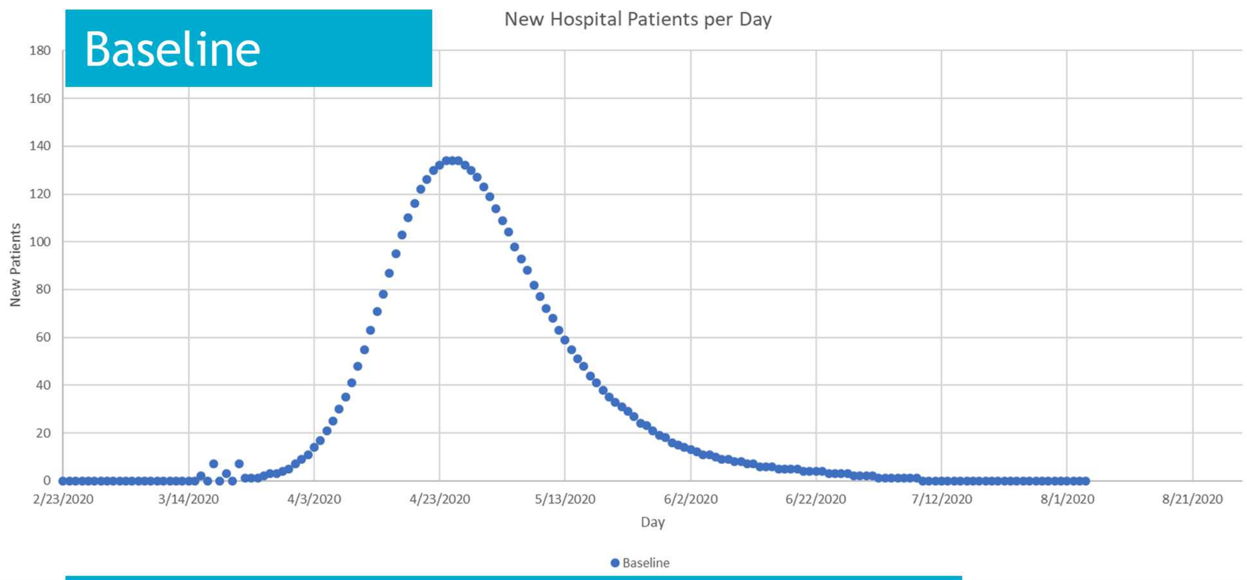
Example Using IHME Mean (number of patients kept constant)



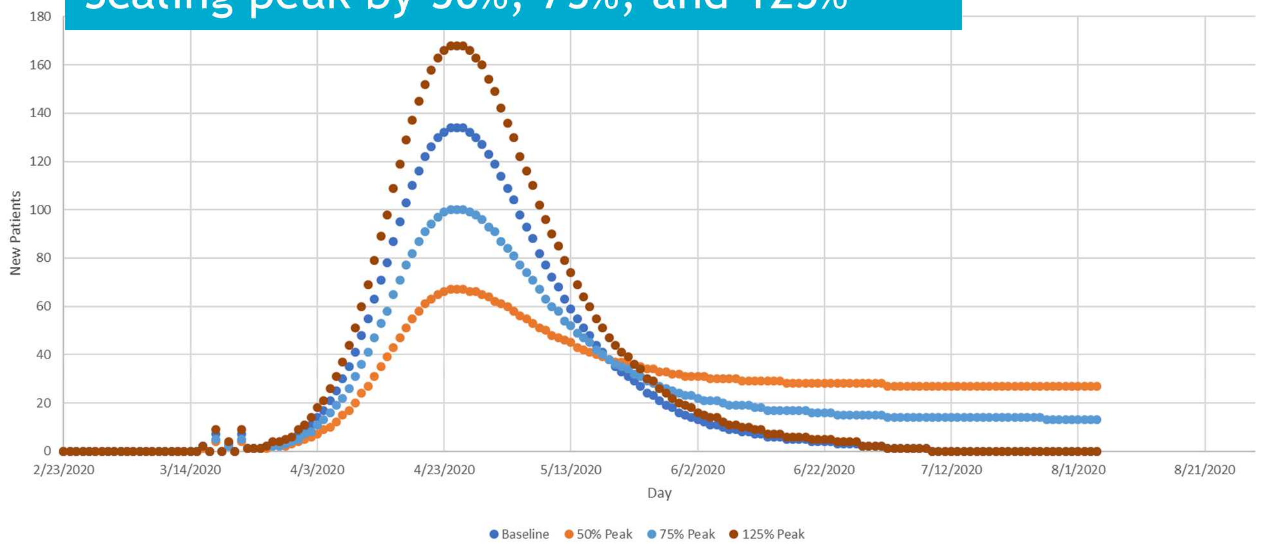
Bending the Curve

Example using IHME mean (number of patients kept constant)

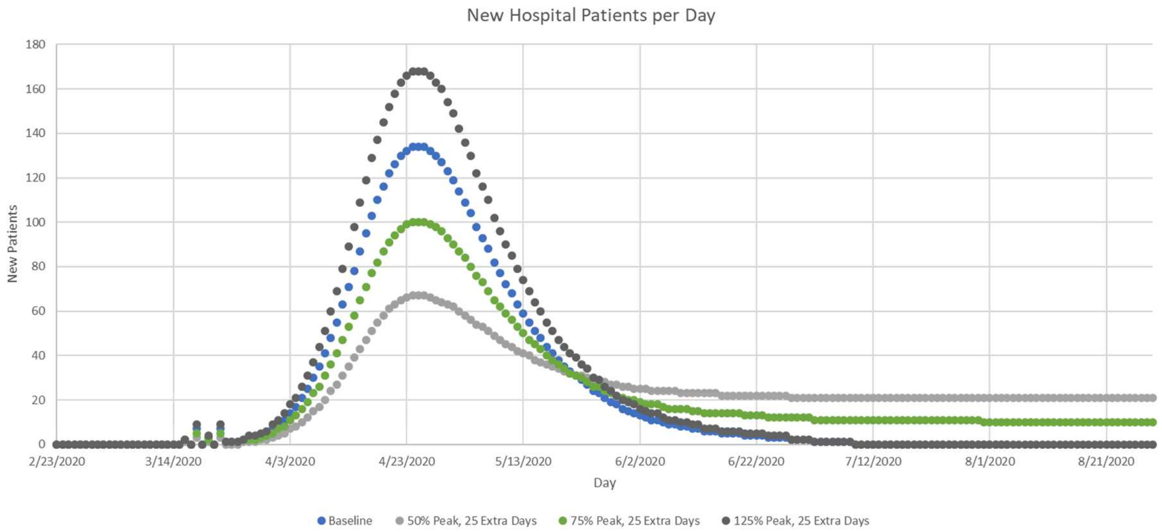
Baseline



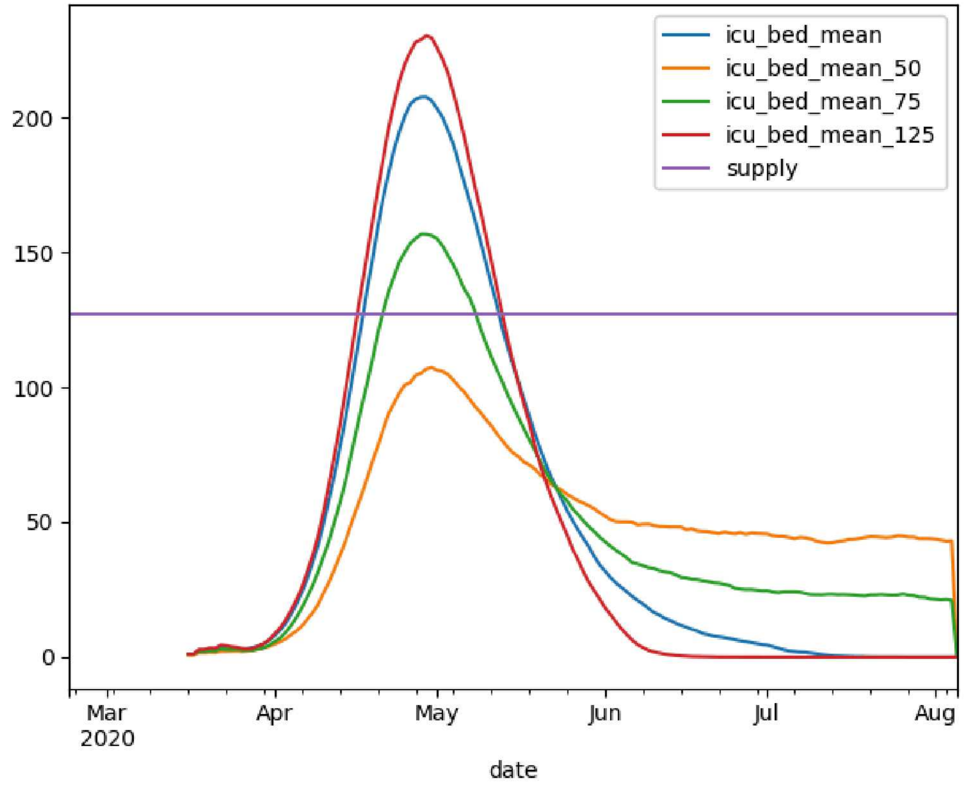
Scaling peak by 50%, 75%, and 125%



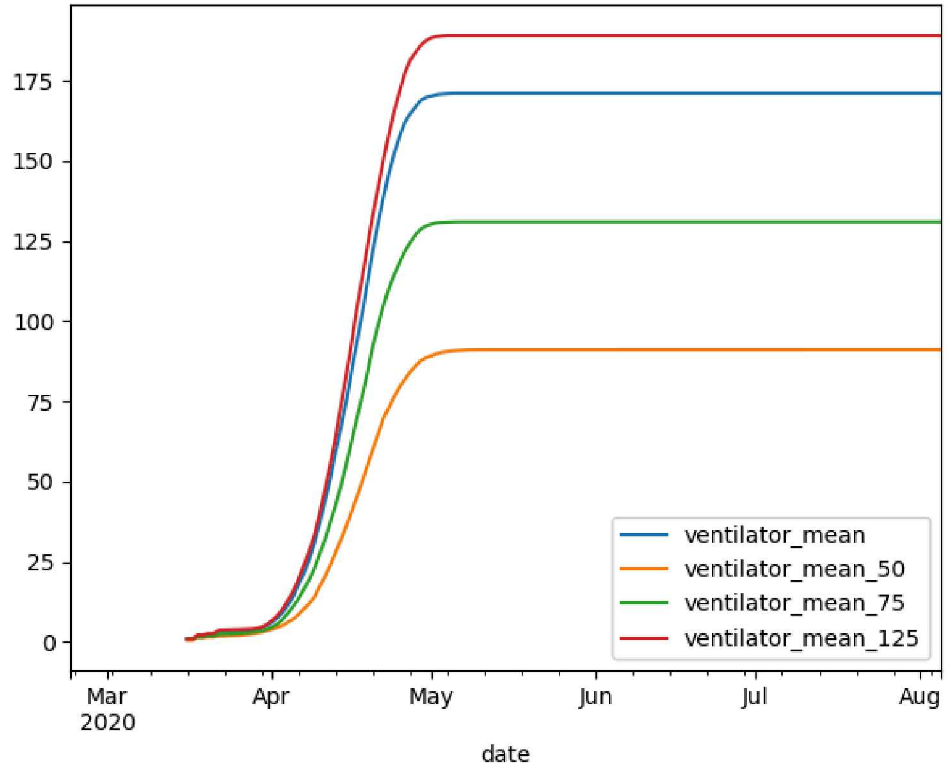
Scaling peak and adding 25 extra days



Results – Analysis 2 – Flatter curves require fewer re-usable assets

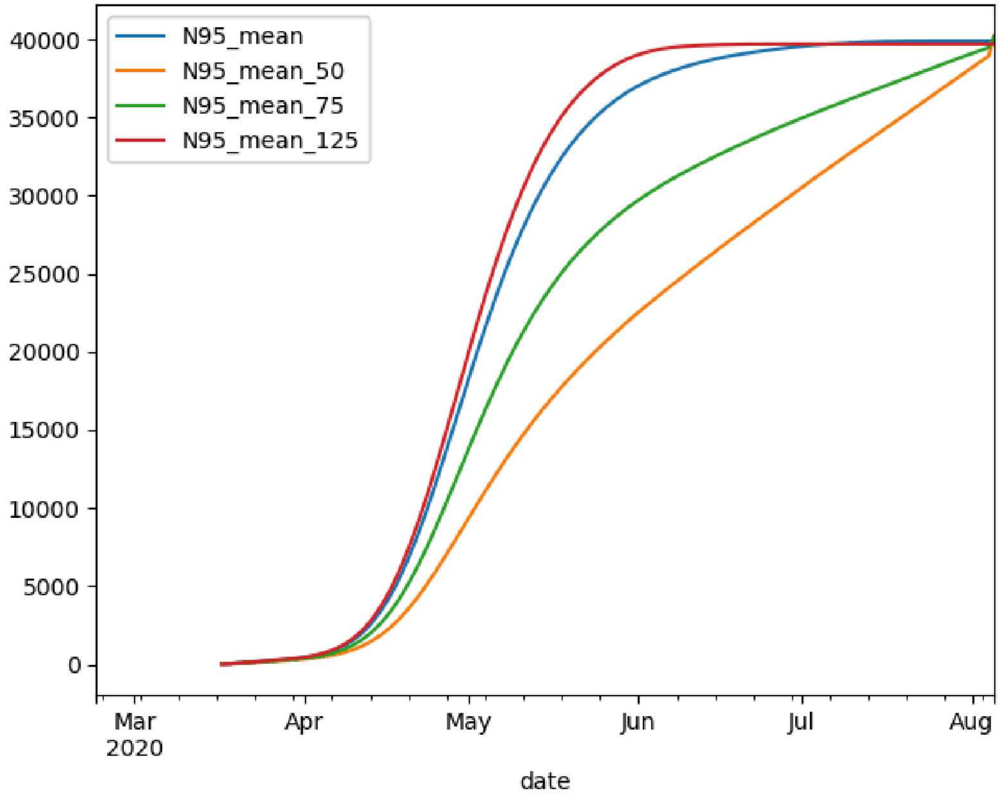


ICU Occupancy



Maximum Number of Ventilators

Results – Analysis 2 – Flatter curves lower required supply rates



Total Number of N95 Masks

Next steps

Application at national- or potentially hospital- scale. Prioritize regional analyses of New York, Chicago, Baltimore, DC, South Florida, New Orleans. Washington State, Los Angeles

Assessing resource risk entails comparing demand and supply. Current databases estimate supplies of some critical assets (ICU beds, possibly staffing) at the hospital level, and larger-scale aggregate data are also available. Probability distributions of resource demands can be compared to these static estimates to derived resource- and time-dependent estimates of resource exhaustion.

Include simple models of resource dynamics (production, consumption, and redistribution). Use to refine resource exhaustion risk as well as the effectiveness of policies or endogenous processes like re-use and sharing in reducing exhaustion risk.

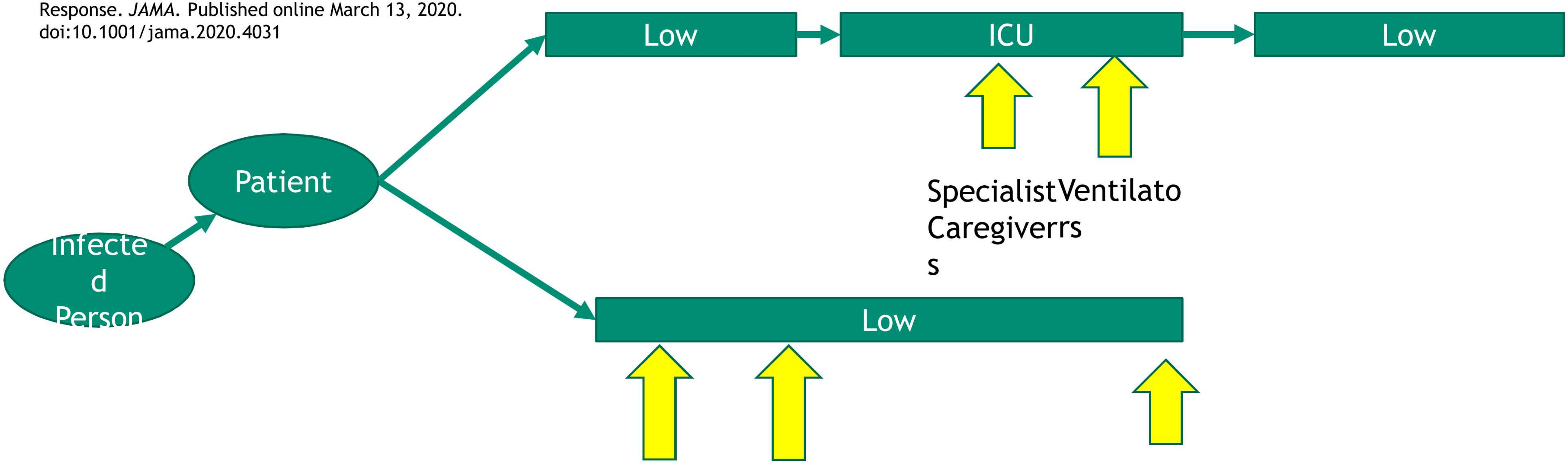
Case studies and hospital expansion plans can be reviewed to define concrete scenarios as well as estimating expansion time constants for more general modeling. Similarly, resource sharing can be studied using case studies as templates, as diffusive processes potentially constrained by political and institutional boundaries. I may also be approached as an optimization problem.

Resource dynamics modeling can help define the efficacy of policies designed to move resources from regions of large current need to regions of growing need. The UQ framework enables the robust evaluation given that the development path of outbreaks in different regions may be highly uncertain.

References

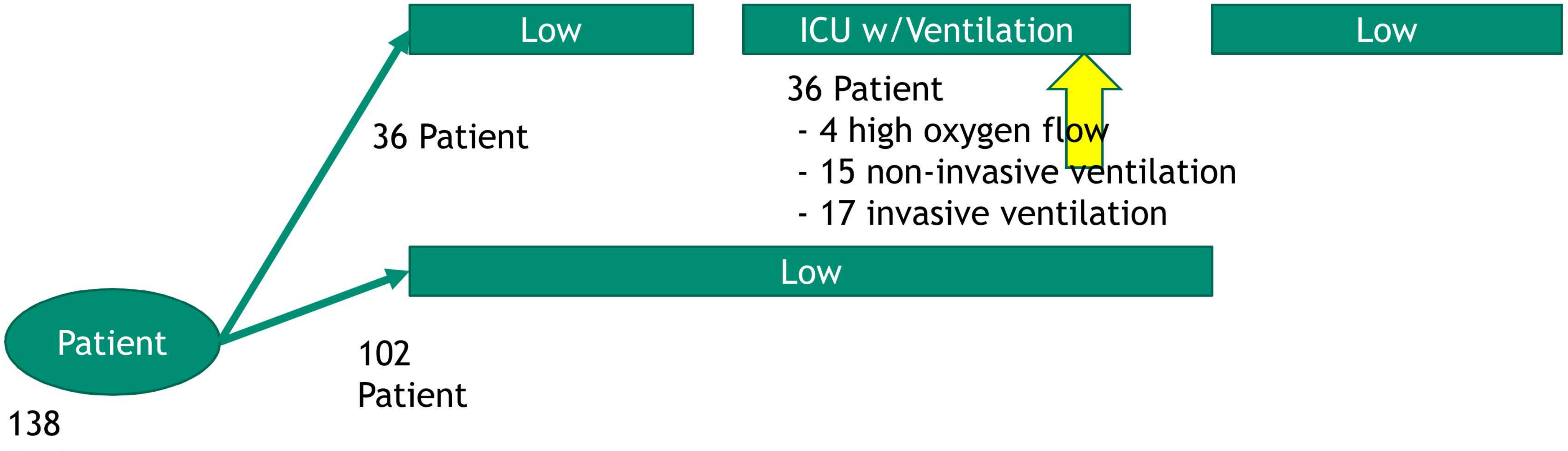
As of March 7, the current total number of patients with COVID-19 occupying an ICU bed (n = 359) represents 16% of currently hospitalized patients with COVID-19 (n = 2217); The proportion of ICU admissions represents 12% of the total positive cases, and 16% of all hospitalized patients. Grasselli G, Pesenti A, Cecconi M. Critical Care Utilization for the COVID-19 Outbreak in Lombardy, Italy: Early Experience and Forecast During an Emergency Response. *JAMA*. Published online March 13, 2020. doi:10.1001/jama.2020.4031

In this single-center case series involving 138 patients with NCIP, 26% of patients required admission to the intensive care unit and 4.3% died.; Wang D, Hu B, Hu C, et al. Clinical Characteristics of 138 Hospitalized Patients With 2019 Novel Coronavirus–Infected Pneumonia in Wuhan, China. *JAMA*. 2020;323(11):1061–1069. doi:10.1001/jama.2020.1585



Guan WJ, Ni ZY, Hu Y, et al; China Medical Treatment Expert Group for Covid-19. Clinical characteristics of coronavirus disease 2019 in China. *N Engl J Med*. doi:10.1056/NEJMoa2002032

Wang D, Hu B, Hu C, et al. Clinical Characteristics of 138 Hospitalized Patients With 2019 Novel Coronavirus–Infected Pneumonia in Wuhan, China. *JAMA.* 2020;323(11):1061–1069. doi:10.1001/jama.2020.1585

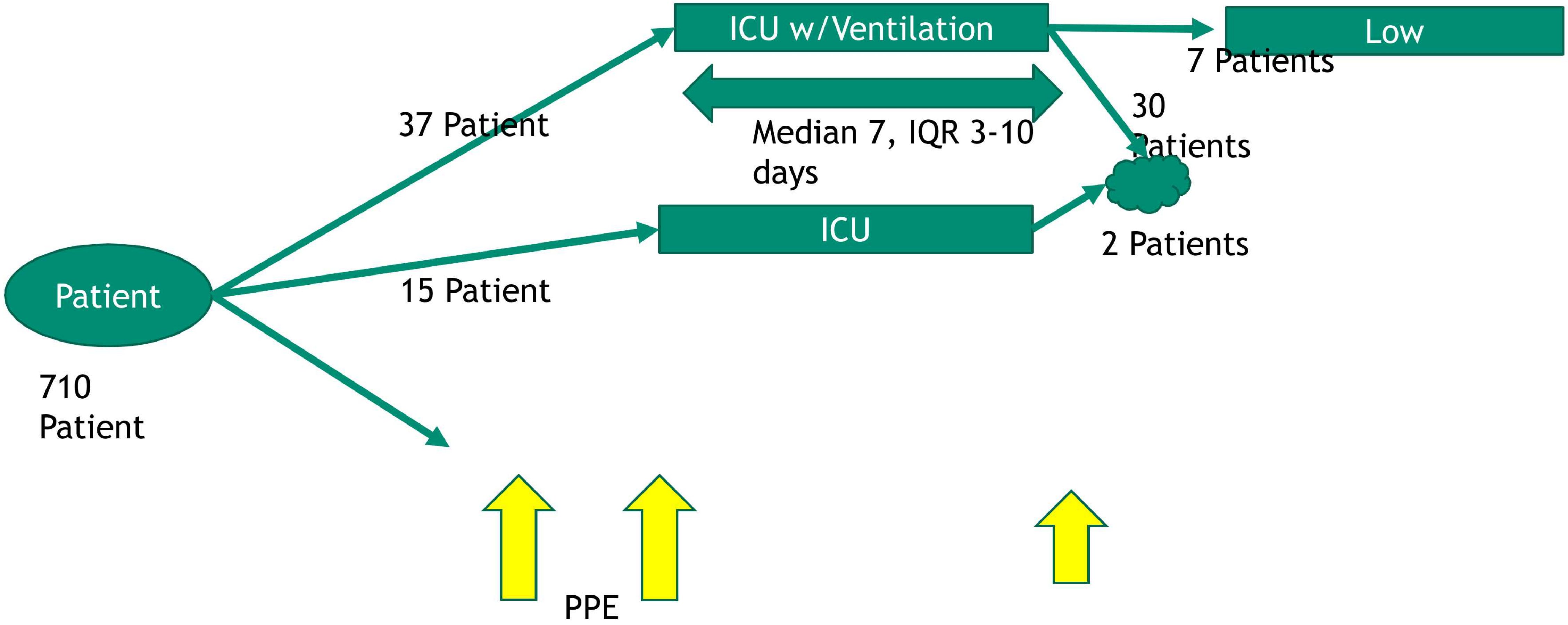


Of 138 hospitalized patients with NCIP, the median age was 56 years (interquartile range, 42-68; range, 22-92 years) and 75 (54.3%) were men. Hospital-associated transmission was suspected as the presumed mechanism of infection for affected health professionals (40 [29%]) and hospitalized patients (17 [12.3%]). Common symptoms included fever (136 [98.6%]), fatigue (96 [69.6%]), and dry cough (82 [59.4%]). Lymphopenia (lymphocyte count, 0.8 × 10^9/L [interquartile range {IQR}, 0.6-1.1]) occurred in 97 patients (70.3%), prolonged prothrombin time (13.0 seconds [IQR, 12.3-13.7]) in 80 patients (58%), and elevated lactate dehydrogenase (261 U/L [IQR, 182-403]) in 55 patients (39.9%). Chest computed tomographic scans showed bilateral patchy shadows or ground glass opacity in the lungs of all patients. Most patients received antiviral therapy (oseltamivir, 124 [89.9%]), and many received antibacterial therapy (moxifloxacin, 89 [64.4%]; ceftriaxone, 34 [24.6%]; azithromycin, 25 [18.1%]), and glucocorticoid therapy (62 [44.9%]). **Thirty-six patients (26.1%) were transferred to the intensive care unit (ICU) because of complications**, including acute respiratory distress syndrome (22 [61.1%]), arrhythmia (16 [44.4%]), and shock (11 [30.6%]). The median time from first symptom to dyspnea was 5.0 days, to hospital admission was 7.0 days, and to ARDS was 8.0 days. Patients treated in the ICU (n = 36), compared with patients not treated in the ICU (n = 102), were older (median age, 66 years vs 51 years), were more likely to have underlying comorbidities (26 [72.2%] vs 38 [37.3%]), and were more likely to have dyspnea (23 [63.9%] vs 20 [19.6%]), and anorexia (24 [66.7%] vs 31 [30.4%]). Of the 36 cases in the ICU, **4 (11.1%) received high-flow oxygen therapy, 15 (41.7%) received noninvasive ventilation, and 17 (47.2%) received invasive ventilation (4 were switched to extracorporeal membrane oxygenation**). As of February 3, 47 patients (34.1%) were discharged and 6 died (overall mortality, 4.3%), but the remaining patients are still hospitalized. Among those discharged alive (n = 47), the median hospital stay was 10 days (IQR, 7.0-14.0).

PPE

Clinical course and outcomes of critically ill patients with SARS-CoV-2 pneumonia in Wuhan, China: a single-centered, retrospective, observational study.

Yang X[1], Yu Y[2], Xu J[2], Shu H[2], Xia J[3], Liu H[1], Wu Y[2], Zhang L[4], Yu Z[5], Fang M[6], Yu T[3], Wang Y[2], Pan S[2], Zou X[2], Yuan S[2], Shang Y[7].



Of 710 patients with SARS-CoV-2 pneumonia, 52 critically ill adult patients were included. The mean age of the 52 patients was 59·7 (SD 13·3) years, 35 (67%) were men, 21 (40%) had chronic illness, 51 (98%) had fever. 32 (61·5%) patients had died at 28 days, and the median duration from admission to the intensive care unit (ICU) to death was 7 (IQR 3-11) days for non-survivors. Compared with survivors, non-survivors were older (64·6 years [11·2] vs 51·9 years [12·9]), more likely to develop ARDS (26 [81%] patients vs 9 [45%] patients), and more likely to receive mechanical ventilation (30 [94%] patients vs 7 [35%] patients), either invasively or non-invasively. Most patients had organ function damage, including 35 (67%) with ARDS, 15 (29%) with acute kidney injury, 12 (23%) with cardiac injury, 15 (29%) with liver dysfunction, and one (2%) with pneumothorax. 37 (71%) patients required mechanical ventilation. Hospital-acquired infection occurred in seven (13·5%) patients.

Severe Outcomes Among Patients with Coronavirus Disease 2019 (COVID-19) — United States, February 12–March 16, 2020 - CDC

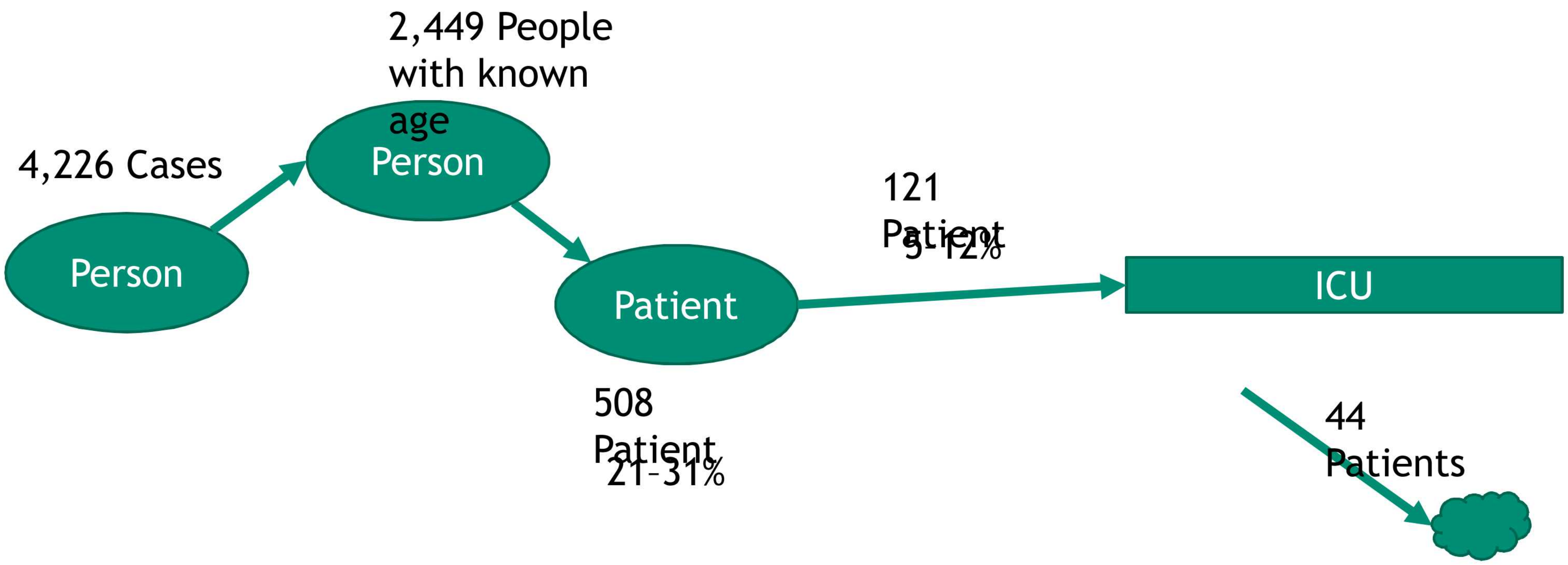
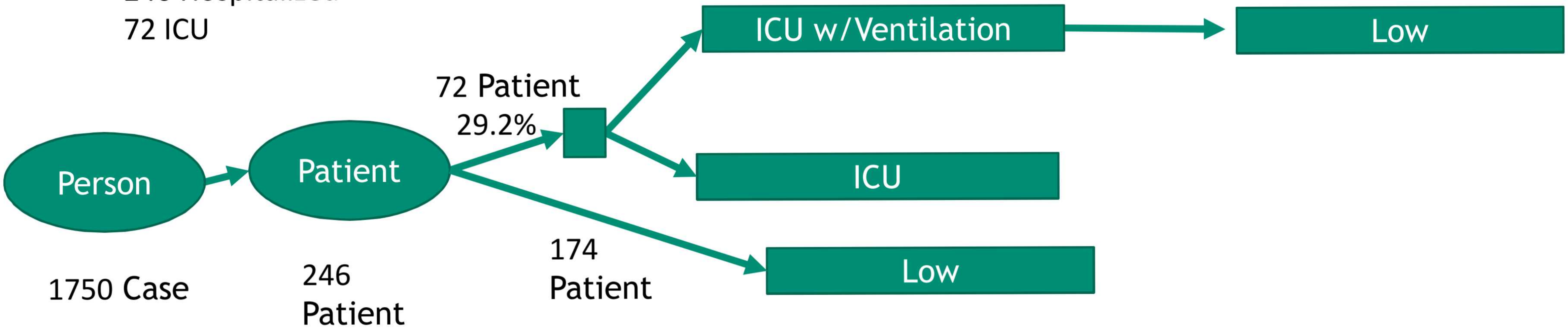
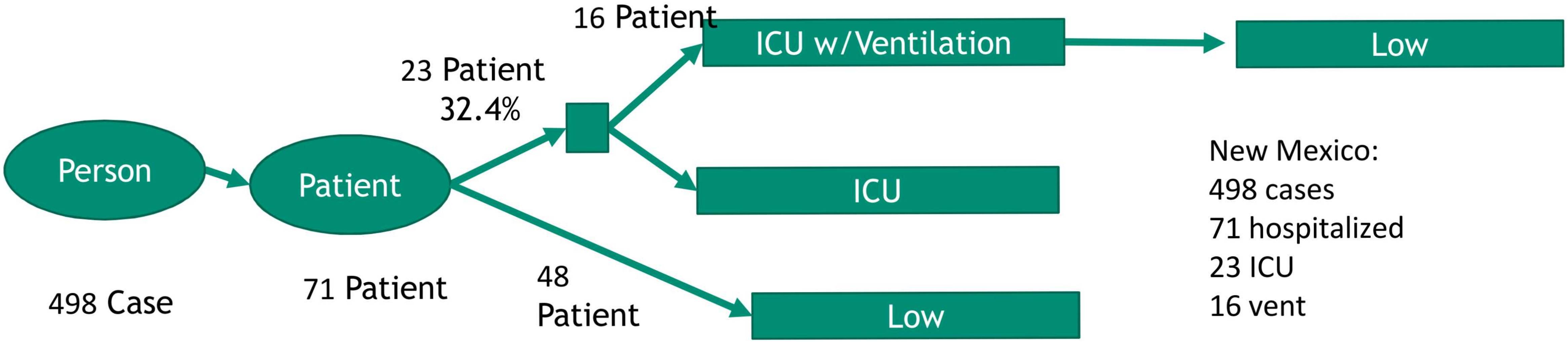


TABLE. Hospitalization, intensive care unit (ICU) admission, and case– fatality percentages for reported COVID–19 cases, by age group — United States, February 12–March 16, 2020 Age group (yrs) (no. of cases) %* Hospitalization ICU admission Case-fatality 0–19 (123) 1.6–2.5 0 0 20–44 (705) 14.3–20.8 2.0–4.2 0.1–0.2 45–54 (429) 21.2–28.3 5.4–10.4 0.5–0.8 55–64 (429) 20.5–30.1 4.7–11.2 1.4–2.6 65–74 (409) 28.6–43.5 8.1–18.8 2.7–4.9 75–84 (210) 30.5–58.7 10.5–31.0 4.3–10.5 ≥85 (144) 31.3–70.3 6.3–29.0 10.4–27.3 Total (2,449) 20.7–31.4 4.9–11.5 1.8–3.4 * Lower bound of range = number of persons hospitalized, admitted to ICU, or who died among total in age group; upper bound of range = number of persons hospitalized, admitted to ICU, or who died among total in age group with known hospitalization status, ICU admission status, or death.

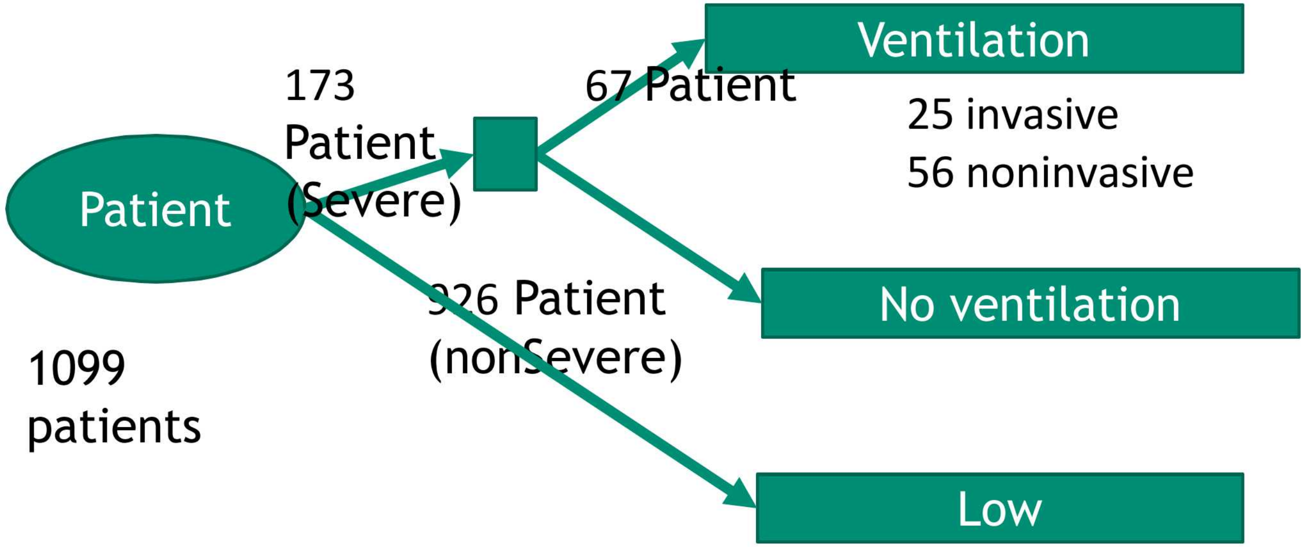
Canada:
1750 Cases with outcomes
246 Hospitalized
72 ICU

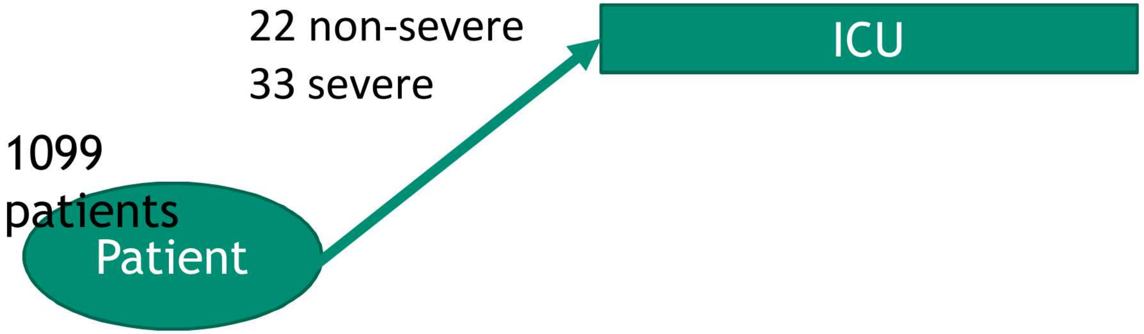




New Mexico:
498 cases
71 hospitalized
23 ICU
16 vent

Clinical Characteristics of Coronavirus Disease 2019 in China
.Wei-jie Guan, Ph.D., Zheng-yi Ni, M.D., et al. doi: 10.1056/NEJMoa2002032; 10.1056/NEJMoa2002032; New England Journal of Medicine; Massachusetts Medical Society; 0028-4793; UR - https://doi.org/10.1056/NEJMoa2002032;2020/04/04





Most patients still hospitalized at publicatio

Estimates of the severity of coronavirus disease 2019:
a model-based analysis

Robert Verity*, Lucy C Okell*, Ilaria Dorigatti*, Peter Winskill*, Charles Whittaker*, Natsuko Imai, Gina Cuomo-Dannenburg, Hayley Thompson, Patrick G T Walker, Han Fu, Amy Dighe, Jamie T Griffin, Marc Baguelin, Sangeeta Bhatia, Adhiratha Boonyasiri, Anne Cori, Zulma Cucunubá, Rich FitzJohn, Katy Gaythorpe, Will Green, Arran Hamlet, Wes Hinsley, Daniel Laydon, Gemma Nedjati-Gilani, Steven Riley, Sabine van Elsland, Erik Volz, Haowei Wang, Yuanrong Wang, Xiaoyue Xi, Christl A Donnelly, Azra C Ghani, Neil M Ferguson*

In the subset of 24 deaths from COVID-19 that occurred in mainland China early in the epidemic, with correction for bias introduced by the growth of the epidemic, we estimated the mean time from onset to death to be 18·8 days (95% credible interval [CrI] 15·7–49·7; figure 2) with a coefficient of variation of 0·45 (95% CrI 0·29–0·54). With the small number of observations in these data and given that they were from early in the epidemic, we could not rule out many deaths occurring with longer times from onset to death, hence the high upper limit of the credible interval. However, given that the epidemic in China has since declined, our posterior estimate of the mean time from onset to death, informed by the analysis of aggregated data from China, is more precise (mean 17·8 days [16·9–19·2]; figure 2).

Using data on the outcomes of 169 cases reported outside of mainland China, we estimated a mean onset-to-recovery time of 24·7 days (95% CrI 22·9–28·1) and coefficient of variation of 0·35 (0·31–0·39; figure 2). Both these onset-to-outcome estimates are consistent with a separate study in China.
23

HOSPITAL_ICU_STAY	TimeInHospitalm(D)
No	0
No	0
No	1
Yes	2
Yes	2
No	2
No	2
	3
Unknown	3
Yes	4
No	4
	4
Unknown	7
No	8
Yes	14
	19

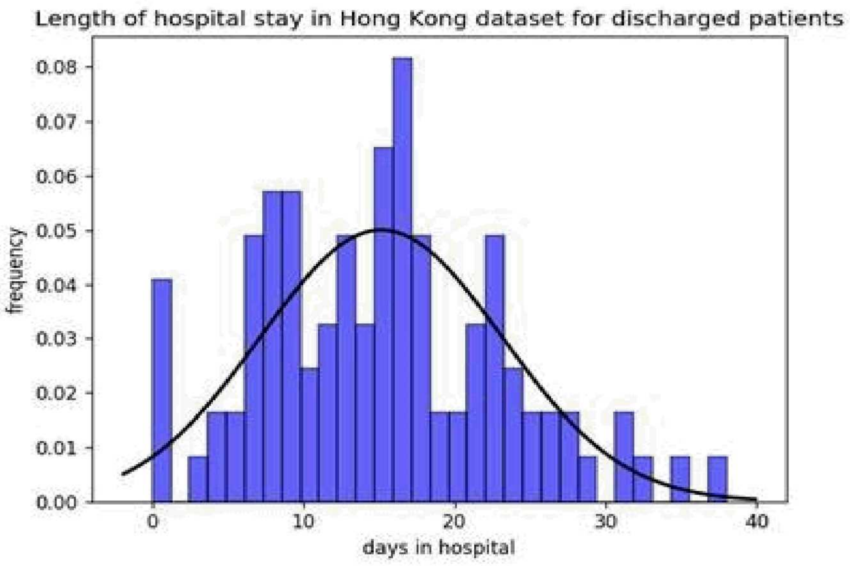
24·7 days (95% CrI 22·9–28·1)

Onset to Recovery

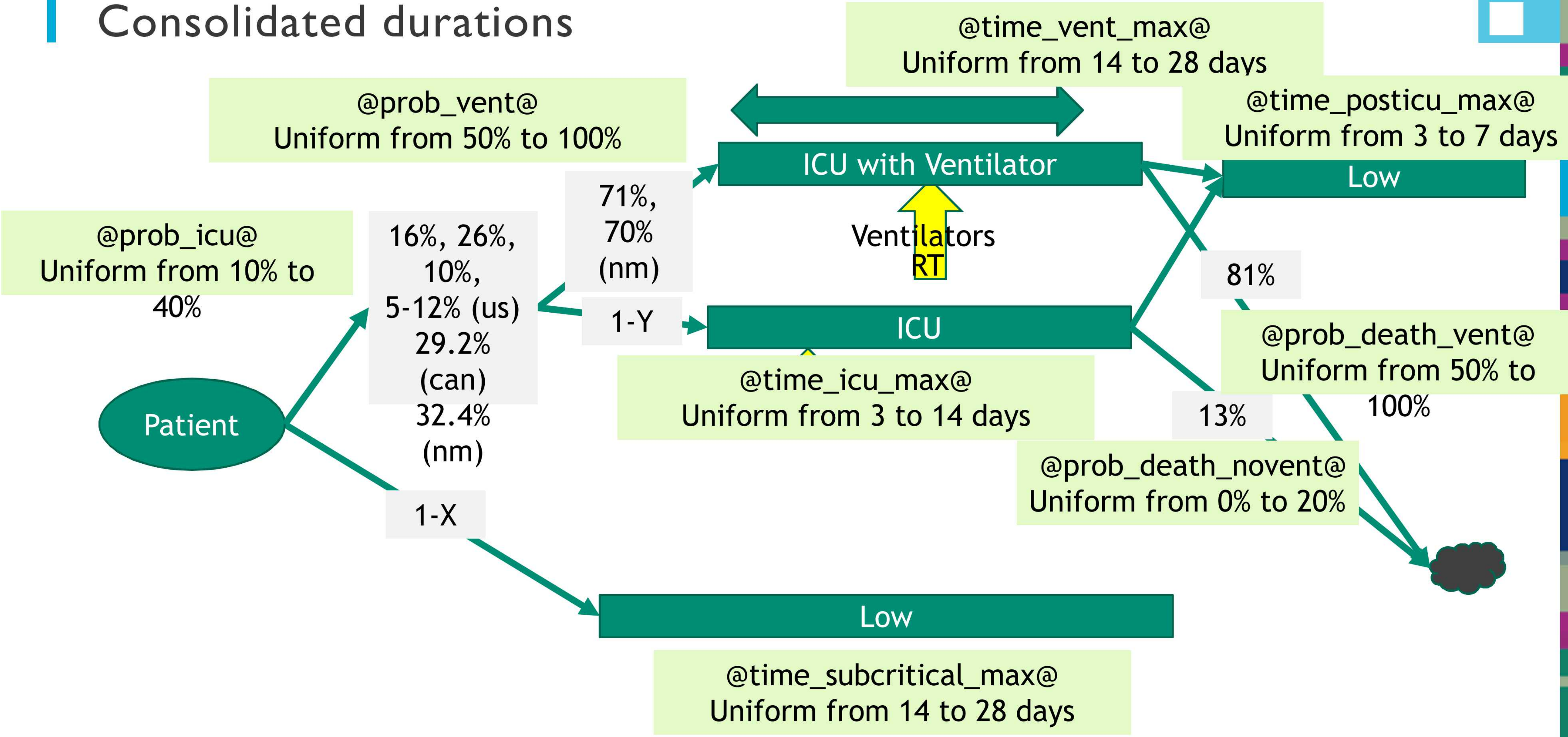
Onset to Death

(mean 17·8 days [16·9–19·2]

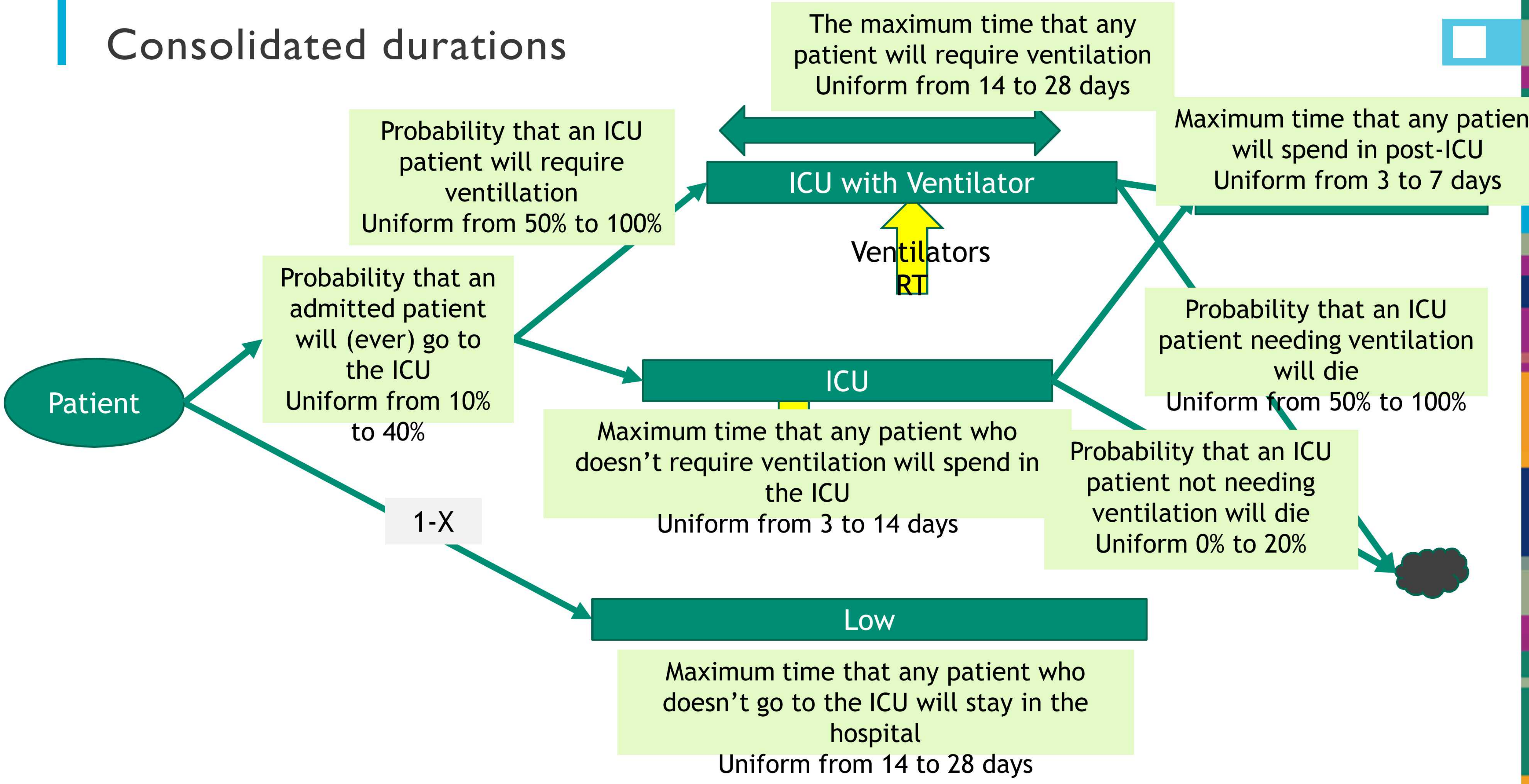
Admission to Discharge



Consolidated durations



Consolidated durations



Resource Use

Local health service planning numbers

Staffing – Number of patients per practitioner

	Context		
Role	**ICU**	**General**	
ICU Nurse	2	N/A	
Doctor	10	20 to 50	Imputed from staffing and nurse/patient ratios assuming 2 docs ICU, 4 general
Nurse	N/A	4 to 10	
Respiratory Therapist			
Lab Tech			
Environmental Services			
Radiology			
ECG Tech			
Healthcare Assistant			

PPE

ICU				
Units used per shift				
Practitioner	Gowns	N95 Mask	Gloves	Face Shield
Floor Nurse	2	1	8	1
ICU Nurse	2	1	12	1
Doctor	2	1	12	1
Healthcare Assistant	2	1	8	1
Environmental Services	4	1	16	1
Lab Tech	2	1	12	1
RT	2	1	8	1
Radiology	2	1	8	1
ECG Tech	2	1	8	1

General				
Units used per shift				
Practitioner	Gowns	N95 Mask	Gloves	Face Shield
Floor Nurse	2	1	8	1
ICU Nurse	2	1	12	1
Doctor	2	1	12	1
Healthcare Assistant	2	1	8	1
Environmental Services	4	1	16	1
Lab Tech	2	1	12	1
RT	2	1	8	1
Radiology	2	1	8	1
ECG Tech	2	1	8	1

Drugs

Review/Evaluation of NMHA data

Staffing – Number of patients per practitioner

	Context	
Role	ICU	General
ICU Nurse	1 to 2	N/A
Doctor	2 to 4	21
Nurse	N/A	4 to 7
Respiratory Therapist	4	
Lab Tech		
Environmental Services		
Radiology		
ECG Tech		
Healthcare Assistant		

PPE

ICU						
Units used per shift						
Practitioner		Gowns	N95 Mask	Gloves	Face Shield	
Floor Nurse						
ICU Nurse		4	4	4	4	
Doctor		1	1	1	1	
Healthcare Assistant						
Environmental Services						
Lab Tech						
RT						
Radiology						
ECG Tech						

General						
Units used per shift						
Practitioner		Gowns	N95 Mask	Gloves	Face Shield	
Floor Nurse		3	3	3	1	
ICU Nurse						
Doctor		1	1	1	1	
Healthcare Assistant						
Environmental Services						
Lab Tech						
RT						
Radiology						
ECG Tech						

Drugs

			Supplies		
		Units used per patient per shift			Comments
Hospital	Practitioner	Sedatives/drugs: Succinylcholine/ rocuronium Etomidate; Propofol Metered Dose Inhalers – Albuterol, (Ventolin); Azithromycin Plaquenil (hydroxychloroquine) Fentanyl; hydromorphine; IV fluids; TPN (Total Parenteral Nutrition) Lipids; dopamine	Equipment intubation tubes, supply tubing, suction catheters; oxygen, oxygen masks, oxygen supply tubing, nebulizing equipment; IV supplies	Context	Drugs and routinely administered meds were separated out from equipment Some drugs are administered more often than others, while equipment may be just 1 per person until they need a new one
Cibola Grants	ICU Nurse	1- 4 (dose dependent)/patient; Maybe 6-8/patient (shortage)	1 or less/patient NA (IV pump)	ICU	4 bed ICU; 21 non-ICU beds
LLMC		1- 4 (dose dependent)/patient;	1 or less/patient	ICU	263 total beds;

Additional Sources

ICU – 12 to 16 per patient per day
GW – 8 per patient per day

Per CDC cited in:
Potential Demand for Respirators and Surgical Masks During a Hypothetical Influenza Pandemic in the United States

Cristina Carias,[1,2] Gabriel Rainisch,[3] Manjunath Shankar,[3] Bishwa B. Adhikari,[3] David L. Swerdlow,[1,4] William A. Bower,[5] Satish K. Pillai,[3] Martin I. Meltzer,[3] and Lisa M. Koonin[6]
[1]National Center for Immunization and Respiratory Diseases (NCIRD), [2]IHRC, Inc, [3]Division of Preparedness and Emerging Infections, National Center for
Emer