Durham University Business School

Maximising patient benefit from triage policies: an empirically informed systems modelling and simulation study

Christos Vasilakis, Li Ding and Dong Li
Wolfson Research Institute, Durham University

Health Festival **"Celebrating Health"**

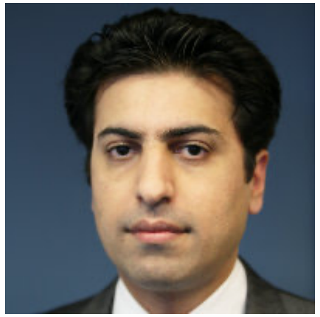
June 28 2023

Outline

- Project Team
- Introduction and Background
- The problem setting
- Our approach and model
- Hospital data and survey
- Numerical and simulation results
- Key takeaway

Project Team




Li Ding | Dong Li | Christos Vasilakis | Navid Izady | Richard Wood

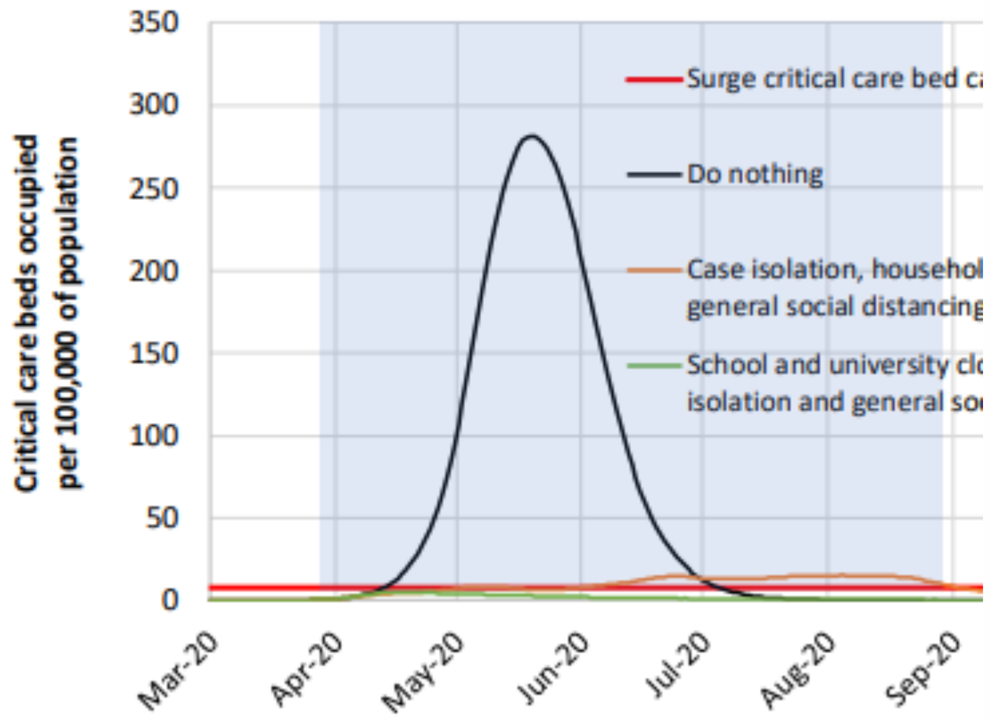
Durham University, Loughborough University, City University, Bath University and NHS

Background and premise

- Recall the start of the pandemic
  - New disease, spreading rapidly
  - Will we have enough hospital beds?
  - Intensive Care capacity?

- Information gap
  - Little information or data
  - Hospitals needed information, and quickly
  - Rapid decisions were required for bed planning
  - Modelling studies informed such decisions

Report 9, Ferguson et al, 16 March 2020

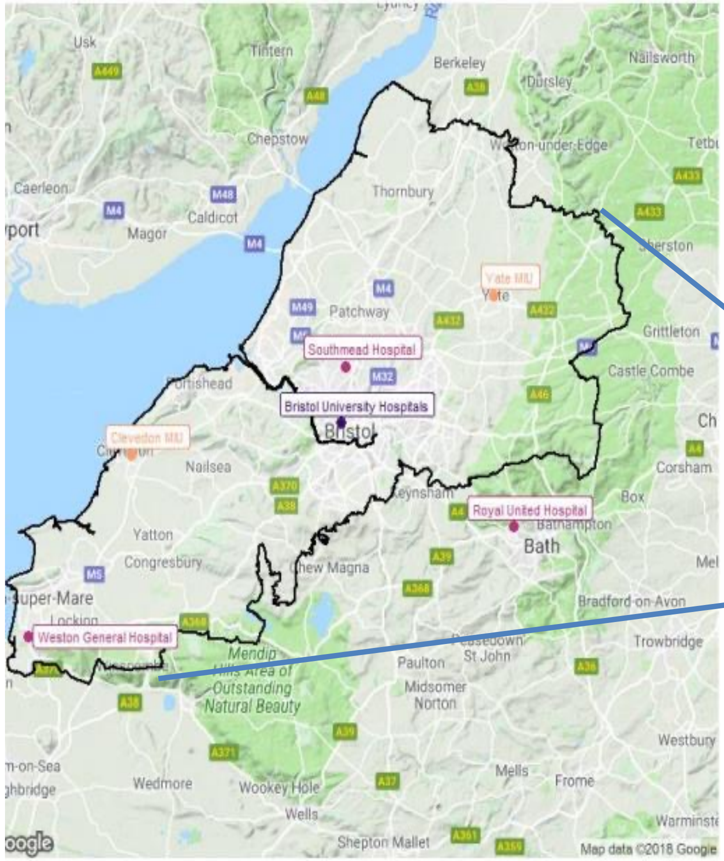


Durham University Business School

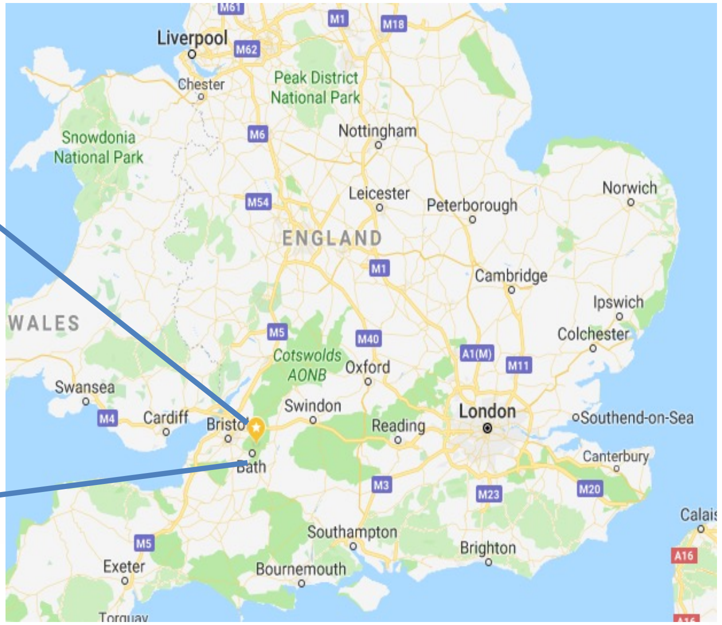
Study setting

ICBs decide what services are needed for local populations; fund providers; ensue services are provided

- population of around 1,000,000
- primarily urban, 16% live in some of the most deprived areas of England
- urgent, emergency, elective hospital care
- maternity, rehabilitation, mental health
- primary and community health services
- total expenditure: £1.615 Billion (2020/21) and rising



NHS
Bristol, North Somerset and South Gloucestershire
Integrated Care Board



Durham University Business School

References

Wood R M, McWilliams C J, Thomas M J, Bourdeaux C P & Vasilakis, C. (2020). COVID-19 scenario modelling for the mitigation of capacity-dependent deaths in intensive care.

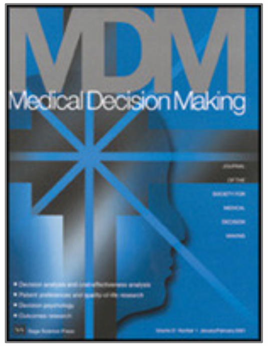
Health Care Management Science 23(3), 315-324

doi.org/10.1007/s10729-020-09511-7

Wood R, Pratt A, Kenward C, McWilliams C, Booton R, Thomas M, Bourdeaux C Vasilakis, C. (2021). The Value of Triage during Periods of Intense COVID-19 Demand: Simulation Modeling Study.

Medical Decision Making 41(4), 393-407

[10.1177/0272989X21994035](https://doi.org/10.1177/0272989X21994035)



https://github.com/nhs-bnssg-analytics GitHub

Study 1

Intensive Care (IC) surge capacity model

- How many deaths could we expect given different levels of bed capacity?
- How can we reduce capacity-dependent deaths?
- Modelling performed during first wave in the UK (Spring 2020)

Health Care Management Science
https://doi.org/10.1007/s10729-020-09511-7

Check for updates

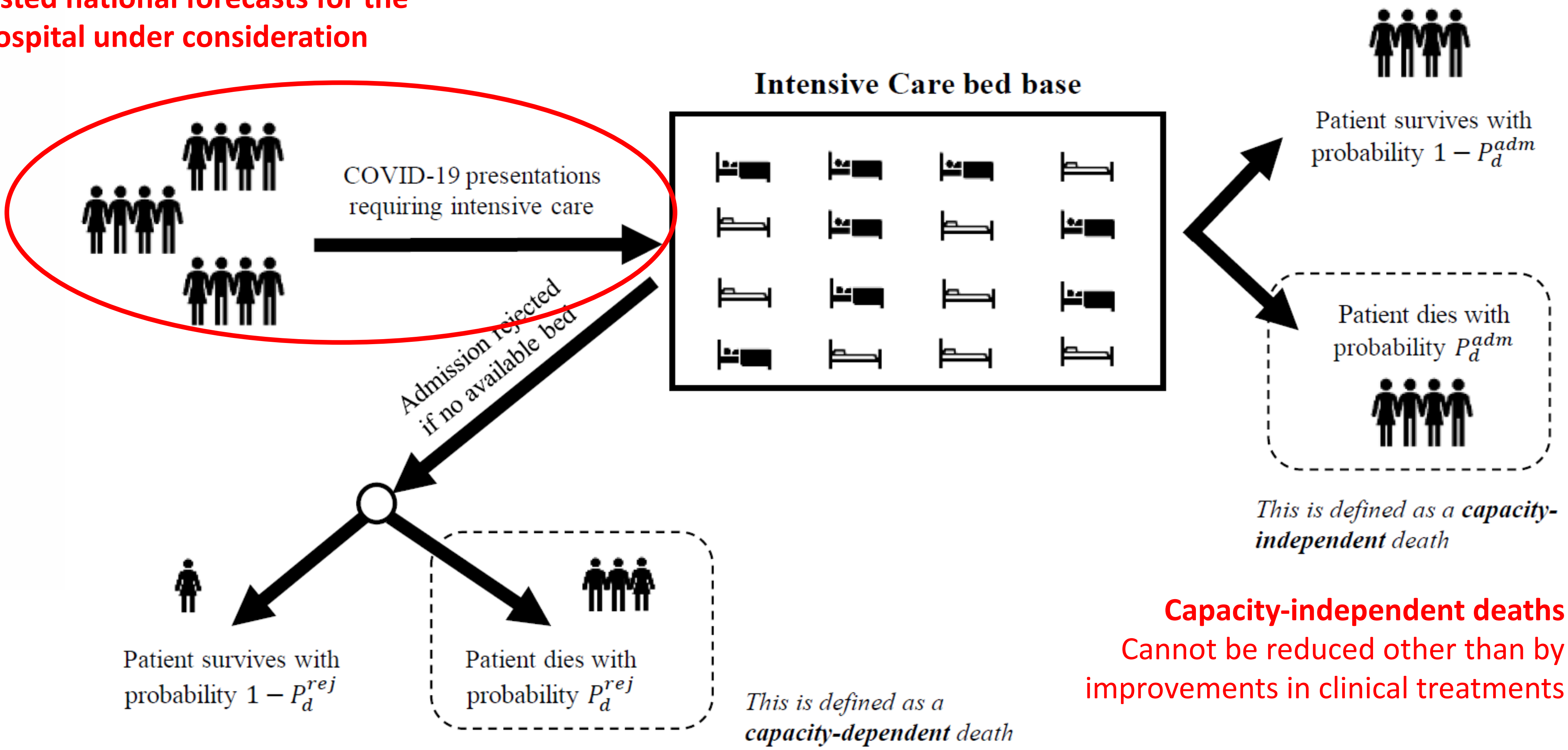
COVID-19 scenario modelling for the mitigation of capacity-dependent deaths in intensive care

Richard M Wood[1,2] · Christopher J McWilliams[3] · Matthew J Thomas[4] · Christopher P Bourdeaux[4] · Christos Vasilakis[2]

Received: 4 May 2020 / Accepted: 11 June 2020

Capacity-(in)dependent deaths

Adjusted national forecasts for the hospital under consideration



Capacity-independent deaths
Cannot be reduced other than by improvements in clinical treatments

Capacity-dependent deaths
Can be mitigated through effective planning

Inputs: length of stay (in IC bed)

- Data available for 4,078 COVID-19 intensive unit admissions in UK (source: ICNARC)
- Information only available for median and IQR
- 2-parameter Gamma distribution fitted by matching these 3 quartiles
- Good fit obtained
- Mean fitted LOS was 8.07 days

	Quartile 1	Median	Quartile 3
Empirical	3.5 days	6.5 days	11 days
Fitted	3.49 days	6.52 days	10.99 days

Inputs: probabilities of death

- Probability of death for patient admitted to IC = **0.507**

  (n=4078, ICNARC data)

- Probability of death for patient refused IC admission = **0.99**

  (assumed, based on clinical judgement)

Baseline conditions

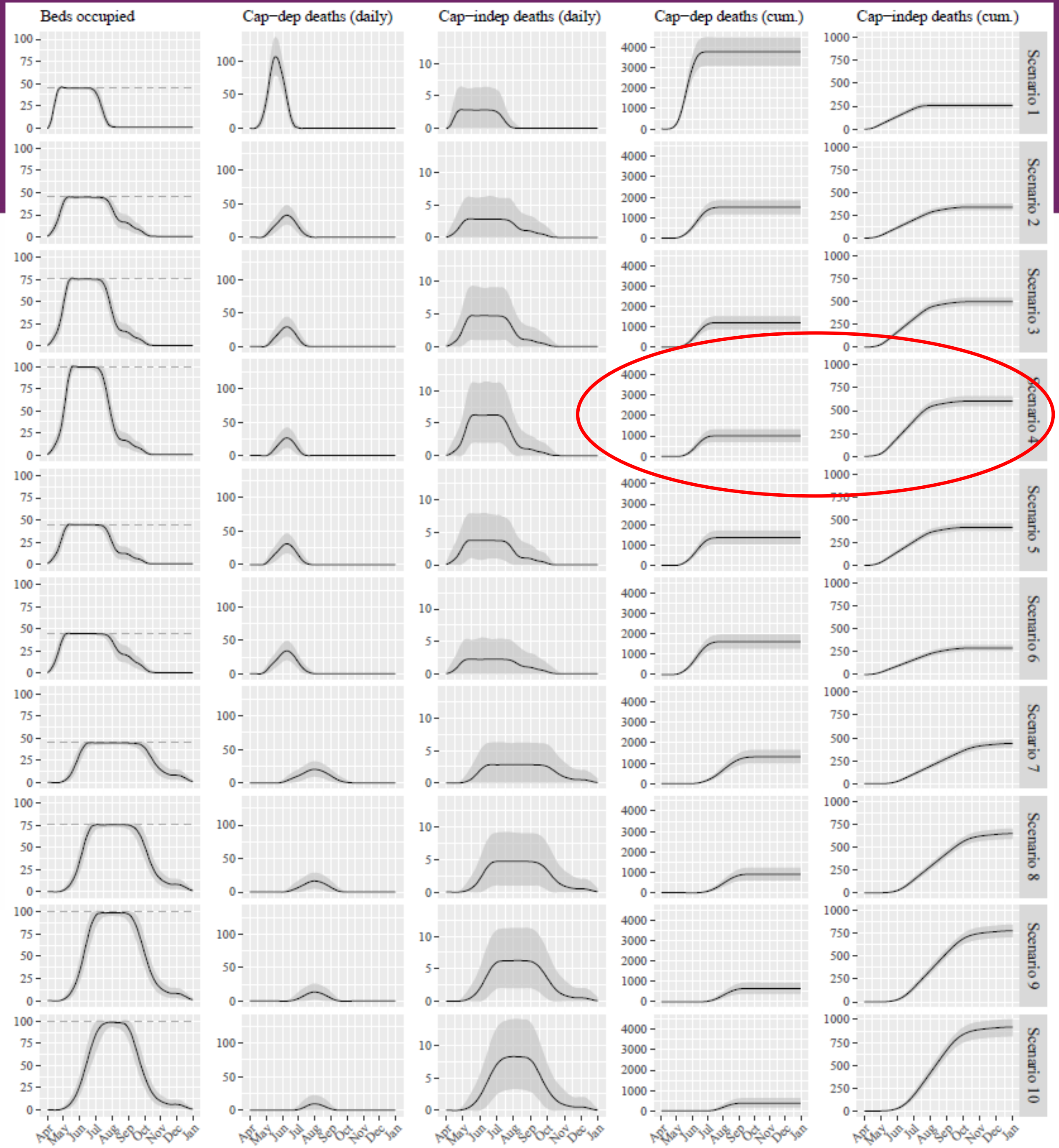
- Inputs calibrated for a major tertiary hospital in Bristol, UK
- Hospital typically had 45 intensive care beds
- Surge capacity could increase number of beds to:
  - 76 beds (first surge level)
  - 100 beds (second surge level)

Results

Total deaths reduced by 14% if IC beds can be increased from 45 to 100

If LOS ↑ 25% then 2.5% more deaths

Capacity-dependent and total deaths much reduced if 'curve can be flattened'



Implications

- Potential gain from converting existing clinical areas to intensive care specification
- Potential gain from investing in efforts to reduce length of stay (e.g. weaning)
- Better understanding of workforce requirements
- Informed the capacity requirements of temporary mortuaries
- Timing and scale of when elective surgeries may resume

Durham University Business School

Study 2

Intensive Care (IC) triage model

- Should access for certain patients be prioritised or restricted?
- How many lives, and life-years, would be saved?
- Modelling performed in advance of second / further waves (late Summer 2020)

Original Research Article

MDM Medical Decision Making

Medical Decision Making
1–15

DOI: 10.1177/0272989X21994035
journals.sagepub.com/home/mdm
SAGE

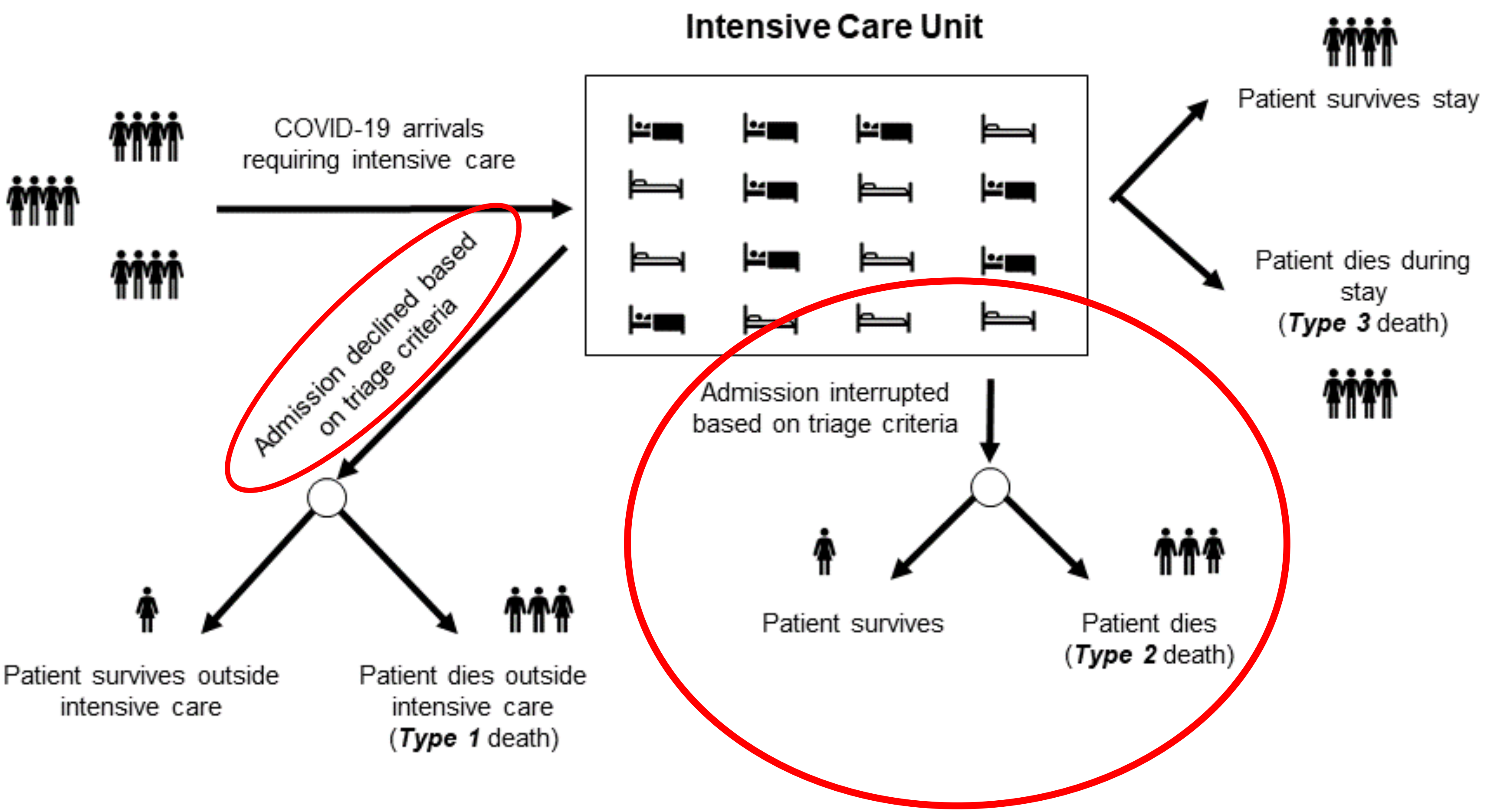
The Value of Triage during Periods of Intense COVID-19 Demand: Simulation Modeling Study

Richard M. Wood, Adrian C. Pratt, Charlie Kenward, Christopher J. McWilliams, Ross D. Booton, Matthew J. Thomas, Christopher P. Bourdeaux, and Christos Vasilakis

Why triage?

- Some patients have a very small chance of benefitting from IC (e.g. very old people, those with severe underlying conditions)
- If capacity was unlimited then everyone could be given a chance
- When IC beds are under pressure then restricting and/or prioritising access (*triaging*) may lead to reduced total number of deaths through admitting those with greatest survival chances
- As well as reducing deaths (increasing lives saved) triage may also increase the number of life-years saved
- This is an ethically charged and sensitive domain
- Our aim was to inform this discussion rather than draw firm conclusions on strategies

Hospital ICU triage and patient outcomes



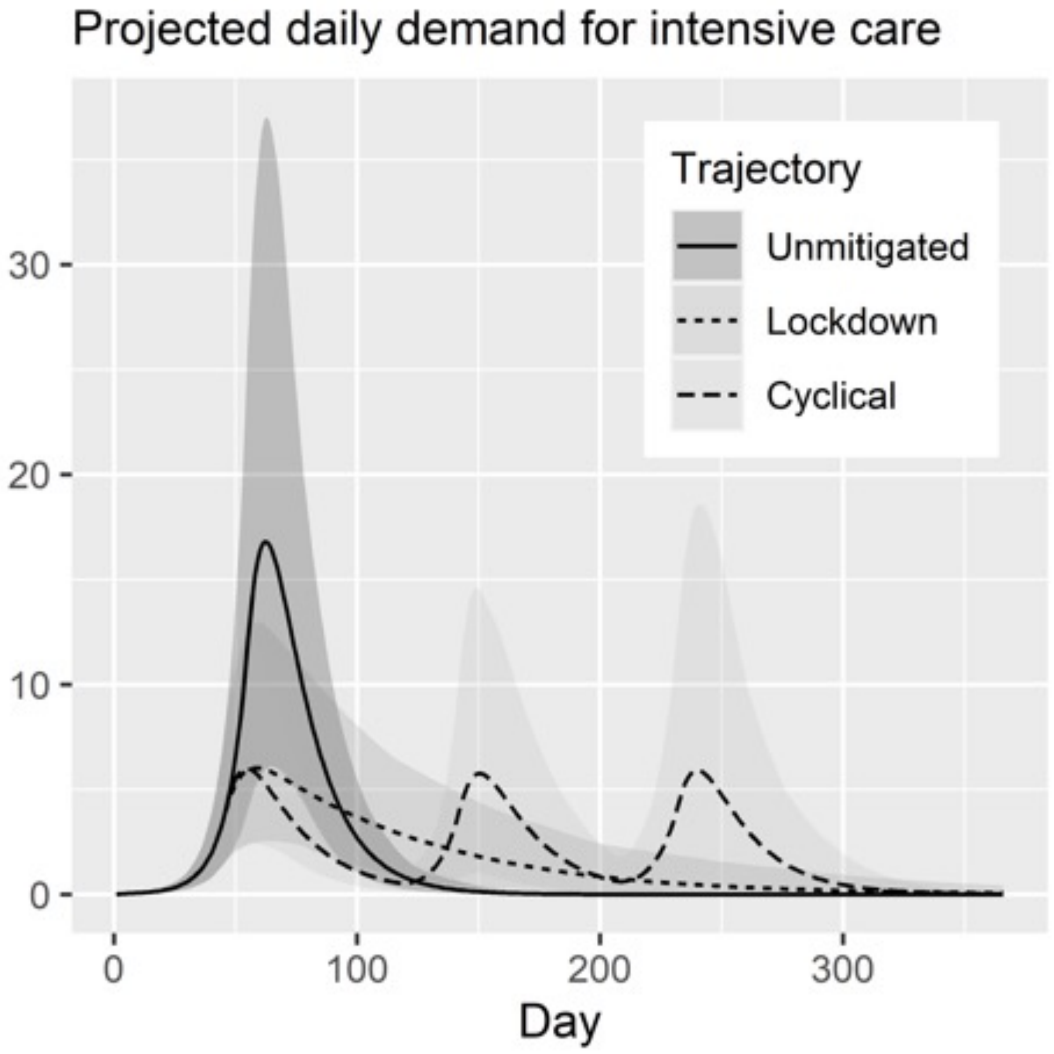
Triage strategies considered

- **Baseline**
  - No triage, first-come first-served
- **Cut-off**
  - Patients above an age threshold are not permitted access
- **Tolerance**
  - Patients above an age threshold are only permitted access if there are *n>1* beds available at the time of demand
- **Interrupt**
  - All patients admitted (if available beds) but any of those above age threshold are discharged early upon arrival of someone below the age threshold who cannot otherwise be admitted

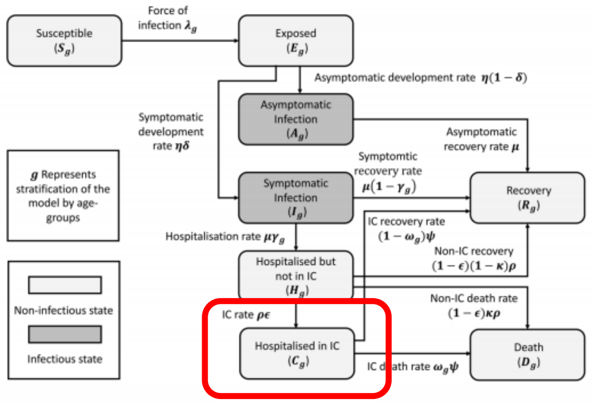
Simulation approach

- Adapted our previously developed discrete event simulation engine (open-source, R based)
- Considered the IC bed base of a hypothetical hospital (20 IC beds)
- Outcome measures: lives saved and life-years saved
- Ensured demand is sufficient to stress the IC bed base

Inputs: arrivals requiring IC



- Investigated three demand scenarios
- Demand trajectories produced by locally developed 'SEIR' model



- This model had been in use for weekly COVID-19 projections in the Bristol healthcare system

Inputs: other parameters

Patient group	Demand proportions[1]	Probability of death if admission declined or interrupted[3]	Probability of death within intensive care[1]	Life-years remaining[2]
Age 16 to 39	0.080	0.990	0.152	54.3
Age 40 to 49	0.136	0.990	0.223	38.0
Age 50 to 59	0.276	0.990	0.345	28.8
Age 60 to 69	0.294	0.990	0.482	20.3
Age 70 to 79	0.183	0.990	0.605	12.7
Age 80 plus	0.031	0.990	0.601	4.9

Admission outcome[1]	Distribution	Parameters		Fitted quartiles (empirical)		
		Shape (α)	Rate (β)	First	Second	Third
Survived	Gamma	0.8904	0.0477	4.7 (5)	12.3 (12)	25.9 (26)
Died	Gamma	1.5488	0.1331	4.8 (5)	9.3 (9)	15.9 (16)

- Calibration through national data[1,2] and assumptions[3]
- National data: ICNARC report 26th June 2020, n = 9505; Office for National Statistics. National life tables (2020)

Results: headlines

- **Cut-off triage strategy**
  - negligible effect on deaths but reduces life-years lost by up to 8.4% (95% CI: 2.6% to 18.7%)
- **Tolerance triage strategy**
  - Slightly better results to the previous one but it does restrict the number of patients admitted to intensive care
- **Interrupt triage strategy**
  - Best performing strategy
  - life-years lost can be reduced by 11.7% (2.8% to 25.8%)
  - any triage benefit is reduced the higher the age threshold is set at
  - triage benefit is also reduced as demand or bed base increases

Summary

- Admitting all patients while reserving the right for early discharge can lead to reduced aggregate losses in lives and life-years
- This makes more effective use of bed availability when compared to other triage methods with more patients at least having the chance to benefit from intensive care
- Very complex ethical considerations, see for example:
  - White & Lo, 2020 https://doi.org/10.1001/jama.2020.5046
  - Vergano et al, 2020 https://doi.org/10.1186/s13054-020-02891-w

Existing principles and triage criteria for resource rationing

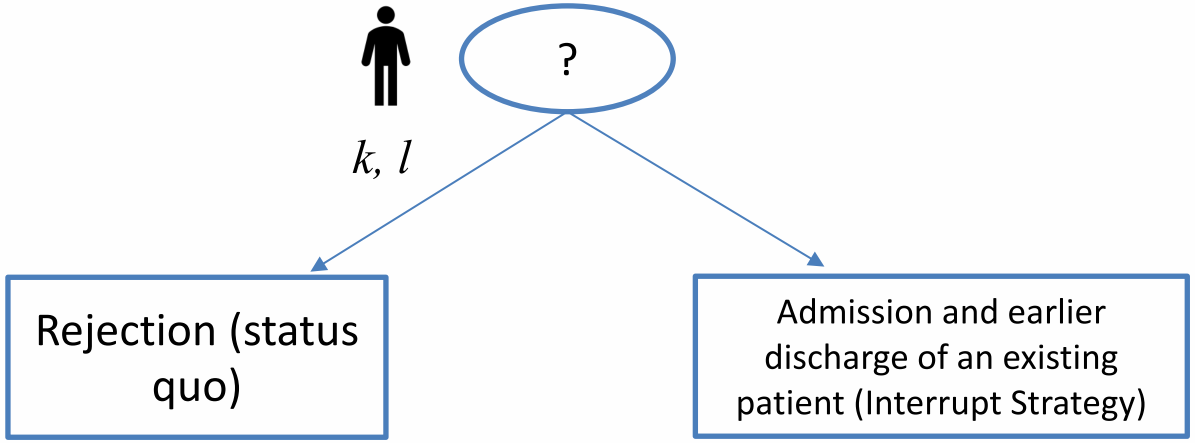
- Existing triage guidelines determine patient priority based on several attributes, including the illness severity and the near-term prognosis after discharge. They focus on individual patients at the time of admission. They do not consider the dynamic illness trajectory of individual patients over the duration of treatment in ICU.
- Further, they ignore the overall mixture of current patient profiles and the uncertainty in the number of patients who become critical ill over time.

Existing principles and triage criteria for resource rationing

- "Maximising the benefits produced by scarce resources, treating people equally, promoting and rewarding instrumental value, and giving priority to the worst off." However, very few policies adopt and operationalise all of these values simultaneously, resulting in suboptimal policies that undermine the principle of fairness in resource rationing

The Problem Setting

- When a seriously-ill Covid-19 patient arrives for intensive care, all ICU beds are fully occupied.



Our approach

- The modelling of the problem as a discrete MDP
- Data input from NHS to show patient progression during their stay in ICU
- Applying decomposition to derive index policies analytically
- Simulation study to evaluating performance
- Open dialogues and questionnaires with health professionals for inputs to the model as well as disseminating findings and generating impact

The model

Discrete Markov Decision Process

- Time epoch: we consider a finite time horizon ***T*** that is discretised into small intervals indexed by *t;*
- State: The number of patients of each category ***k*** and severity level ***l*** in ICU. The state space is
$$\Omega = \{\mathbf{x} : \sum_k \sum_l x_l^k \leq M\}$$
- Actions: Admit/reject a new patient; status quo/discharge a current patient. $a_l^k \in \{0,1\}, \forall k, l.$
- One step transition probability from *x* to *x'* depends on the arrival *e* and the action *a*

The model

- One step cost:

$$c(\mathbf{x}, \mathbf{e}, \mathbf{a}) = \sum_k y^k (x_L^k + e_L^k - a_L^k) q_{L,L+1}^k + \sum_k \sum_l y^k a_l^k \phi_l^k + h \sum_k \sum_l (1 - e_l^k) a_l^k.$$

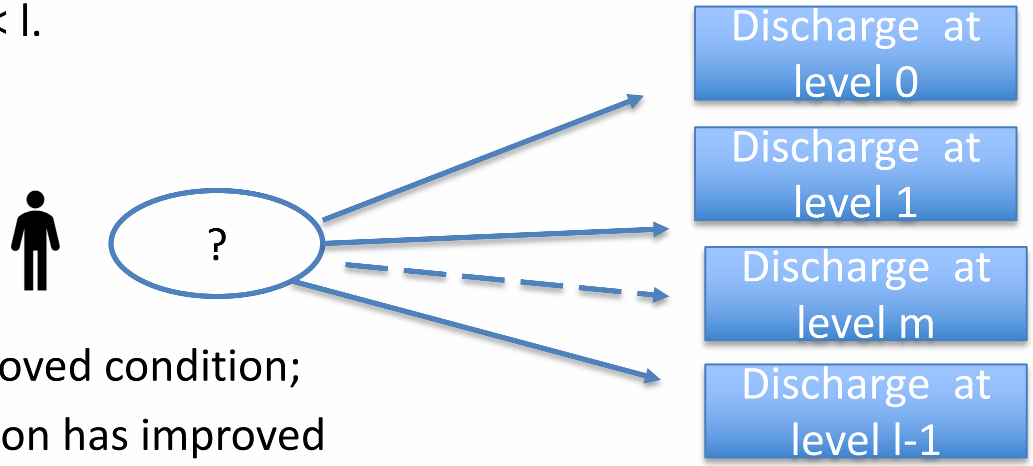
- Policy: Our objective is to find such a policy that minimises the total cost (i.e., expected life-years lost) over time horizon T.

$$V^\pi(\mathbf{0}) = \mathbb{E}\left[\sum_{t=1}^{T-1} c(\mathbf{x}_t, \mathbf{e}_t, \pi(\mathbf{x}_t)) + g(\mathbf{x}_T)\right]$$

Decomposition

- Decomposed into a single patient problem.

Suppose that at each patient arrival, not only must a decision made whether to admit or not, but also the severity level at which the patient will be discharged. If the patient arrival is at level l, then the chosen severity level upon discharge (m) is restricted to the range 0<= m< l.



Underlying assumptions:

Generally speaking, ICU stay will result in improved condition;

Patients are only discharged after their condition has improved

Remarks

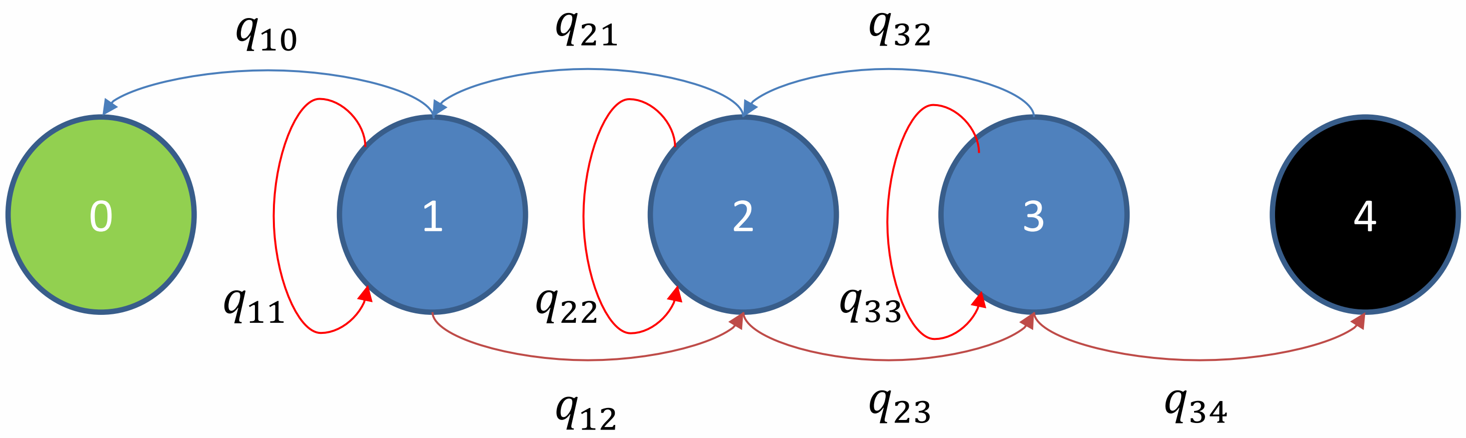
- Bed usage rate *W* is introduced in deriving index policy. Now the total number of beds in ICU are relaxed. *W* have two sided values: system value and shadow value
- It is relatively straightforward to show when system *W* increases, index policy for triage are more likely to reject a new patient. When system W=0, no patient shall be earlier discharged before their time.
- The maximum shadow *W* for admitting a single patient in a specific category and severity level shall be determined by the **relative benefit** obtained from her ICU stay as well as her **length of stay**.

Hospital Data : Descriptive Summary

Two intensive care units at UHBW NHS trusts 17/03/2020 to 24/12/2021					First Mode of Ventilation after Admission		
Age	**n**	**Proportion**	**LoS**	**Mortality**	**SuppO2+RA**	**NIMV**	**IMV**
60+	122	45%	11	48%	19%	54%	27%
under 60	151	55%	12	19%	22%	44%	34%

Durham University Business School

A Markov Chain Model for tracking Covid-19 Patient Severity at ICU



- We use the type of breathing support provided for patients for tracking the progress of patients' disease while in the ICU.

Markov Chain Model

Initial State	Transitions From/To	RA	SuppO2	NIMV	IMV	Death	Discharged	Total
2	RA	724	49	5	0	3	11	792
27	SuppO2	60	5569	670	33	7	53	6392
58	NIMV	6	730	12288	244	19	2	13289
44	IMV	1	17	268	18396	34	2	18718
131	Total	791	6365	13231	18673	63	68	39191

Table 1 Four-stage pathways for patients 60 years old and over.

Initial State	Transitions From/To	RA	SuppO2	NIMV	IMV	Death	Discharged	Total
2	RA	742	74	4	0	2	18	840
25	SuppO2	90	6613	977	46	4	82	7812
77	NIMV	5	1068	12436	195	7	12	13723
38	IMV	0	32	229	15438	14	3	15716
142	Total	837	7787	13646	15679	27	115	38091

Table 2 Four-stage pathways for patients under 60 years old.

Markov Chain Probabilities

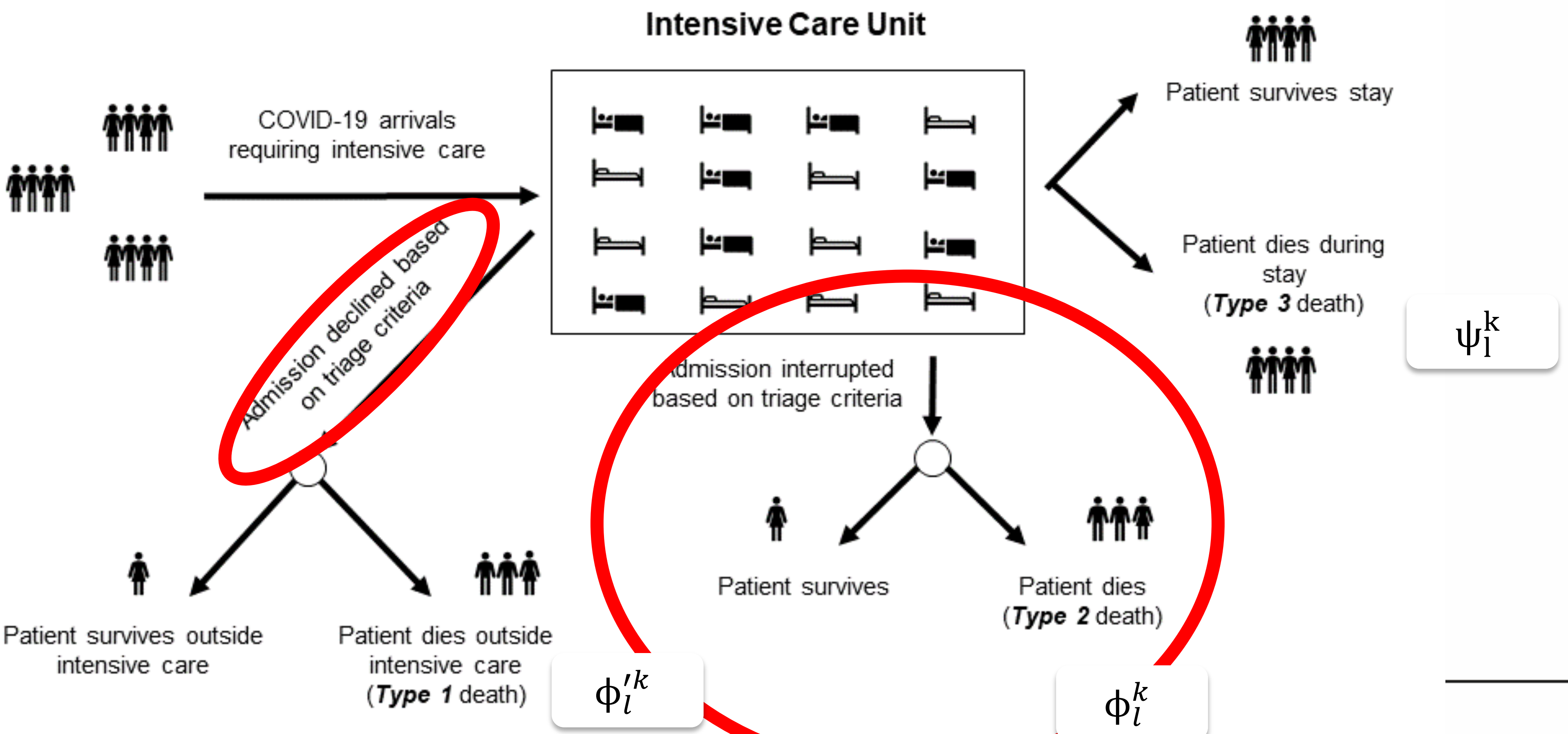
Initial State Prob	Transitions From/To	SuppO2+RA	NIMV	IMV	Death	Discharged
0.221	SuppO2+RA	0.896	0.094	0.000	0.000	0.010
0.443	NIMV	0.056	0.923	0.021	0.000	0.000
0.336	IMV	0.000	0.014	0.982	0.003	0.000

Table 3 Transition probabilities for three initial states 60 years old and over.

Initial State Prob	Transitions From/To	SuppO2+RA	NIMV	IMV	Death	Discharged
0.190	SuppO2+RA	0.873	0.114	0.000	0.000	0.013
0.542	NIMV	0.080	0.903	0.017	0.000	0.000
0.268	IMV	0.000	0.015	0.984	0.002	0.000

Table 4 Transition probabilities for three initial states under 60 years old.

Patient outcomes and mortalities



Probability elicitation of patient mortality

- The mortalities and length of stay of a single patient if admitted can be calculated from ICU patients Markov Chain matrix.
- However, the mortalities of a patient rejected/earlier discharged by ICU are rarely reported in either literature or practice.
- Relative risk RR: a ratio of mortalities of admission to mortalities of rejection to ICU RR = ψ_l^k / ϕ_l^k
- Estimate the value RR via questionnaire among intensive care physicians.

The Questionnaire

- ## Scenario one:

"A COVID patient has been referred to ICU from the medical assessment unit. When relevant patient characteristics have been considered (e.g. age, sex, SOFA, APACHE-II, type of admission etc. . .), their predicted mortality in ICU is 0.5 if admitted."

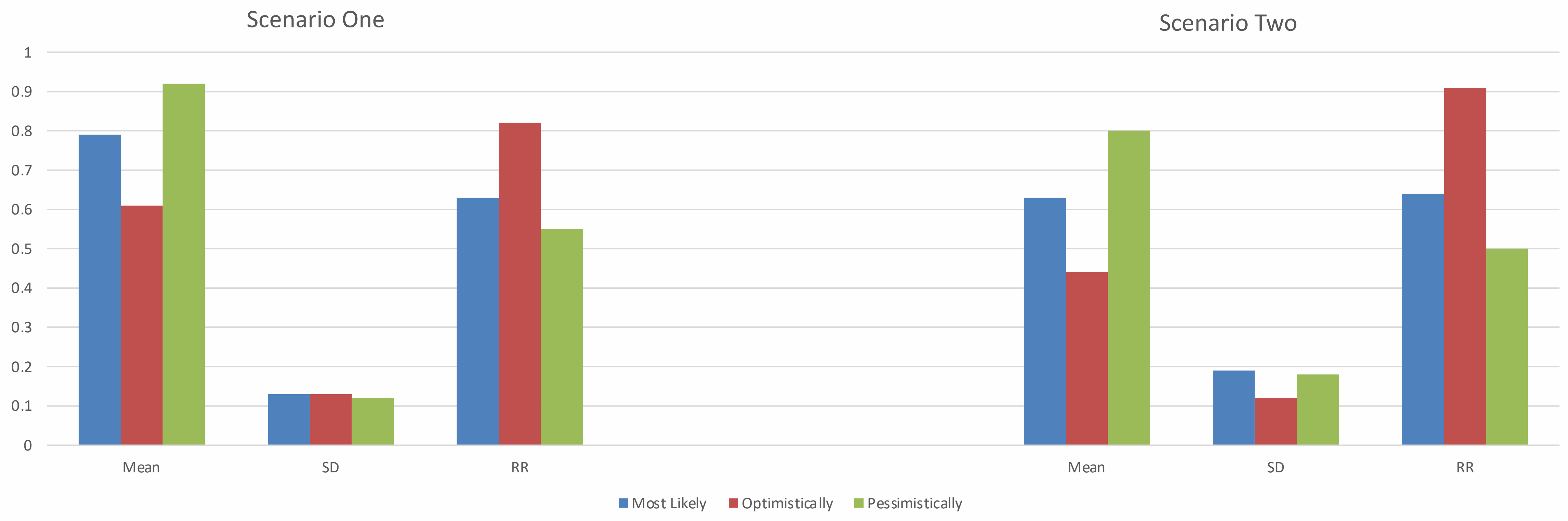
Physicians were asked If the patient was denied admission to ICU for some reason (e.g. due to full capacity), what the best estimate of their new mortality probability is in the order of mostly likely, optimistically and pessimistically.

- ## Scenario Two:

"The same COVID patient has been admitted and is now receiving ICU treatment. Their within-ICU mortality probability is now predicted to be 0.4 if continuously treated in ICU."

Physicians were asked If the patient was prematurely discharged for some reason (e.g., the better prognoses of other admitted/waiting patients), what the best estimate of their new mortality probability is in the order of mostly likely, optimistically and pessimistically.

The results of the questionnaire



Summary

- The modelling approach and decomposition method have operationalised the first three values underlying fairness principle. The numerical results will evidence how the index policy help with those worst off.
- Our index policy developed is forward looking in nature.
- The patient data from UHBW is in line with national data from ICNARC.
- The Markov chain calibrated from the hourly ICU data provides a reasonably accurate model of disease progression.
- Relative Risk (RR) derived from questionnaire among ICU consultants provides a base to assign patient mortalities of rejection and of earlier discharge.

Alternative Triage Strategies

First Come First Serve (FCFS)

- The baseline

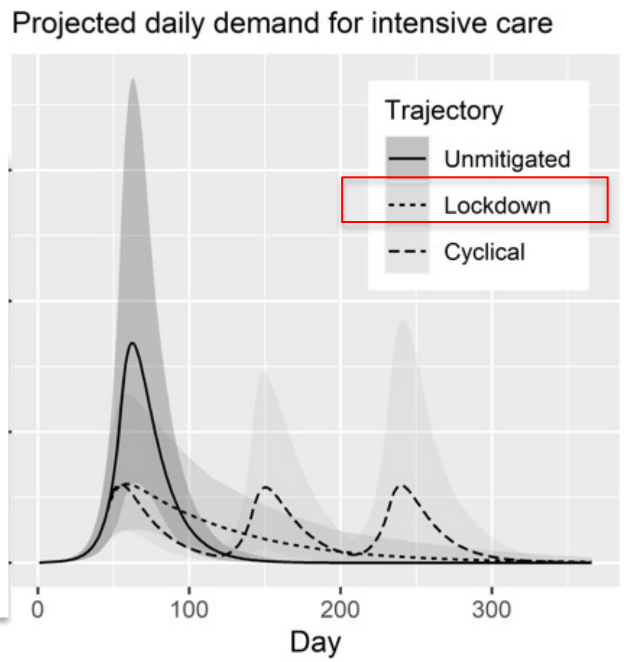
Interrupt

- All patients admitted if there are available beds.
- Otherwise, any of those further below the threshold is discharged upon arrival of someone closer to the threshold. The threshold is defined as the extra life-years saved if being admitted compared to being denied.

Index policy

- Calculate a numerical score (i.e., an index) for each patient, which considers the penalty incurred for early discharges.
- All patients admitted if there are available beds.
- Otherwise,
  - any of those in the ICU with the highest index is discharged upon arrival of someone with a lower index.
  - If the arriving patient has the highest index, they are denied admission.

Simulation Study – The Settings



Patient Category	Patient Level	Life-years remaining	Demand proportion
under 60	SuportO2+RA	35.5	0.0911
under 60	NIMV	35.5	0.2597
under 60	IMV	35.5	0.1282
60+	SuportO2+RA	16.6	0.1153
60+	NIMV	16.6	0.2307
60+	IMV	16.6	0.175

catetory	l_from	l_to	probability
1	1	0	0.0133
1	1	1	0.8729
1	1	2	0.1138
1	2	1	0.0798
1	2	2	0.9027
1	2	3	0.0175
1	3	2	0.0146
1	3	3	0.9837
1	3	4	0.0017

catetory	l_from	l_to	probability
2	1	0	0.0095
2	1	1	0.8961
2	1	2	0.0944
2	2	1	0.0561
2	2	2	0.9231
2	2	3	0.0208
2	3	2	0.0143
2	3	3	0.9823
2	3	4	0.0034

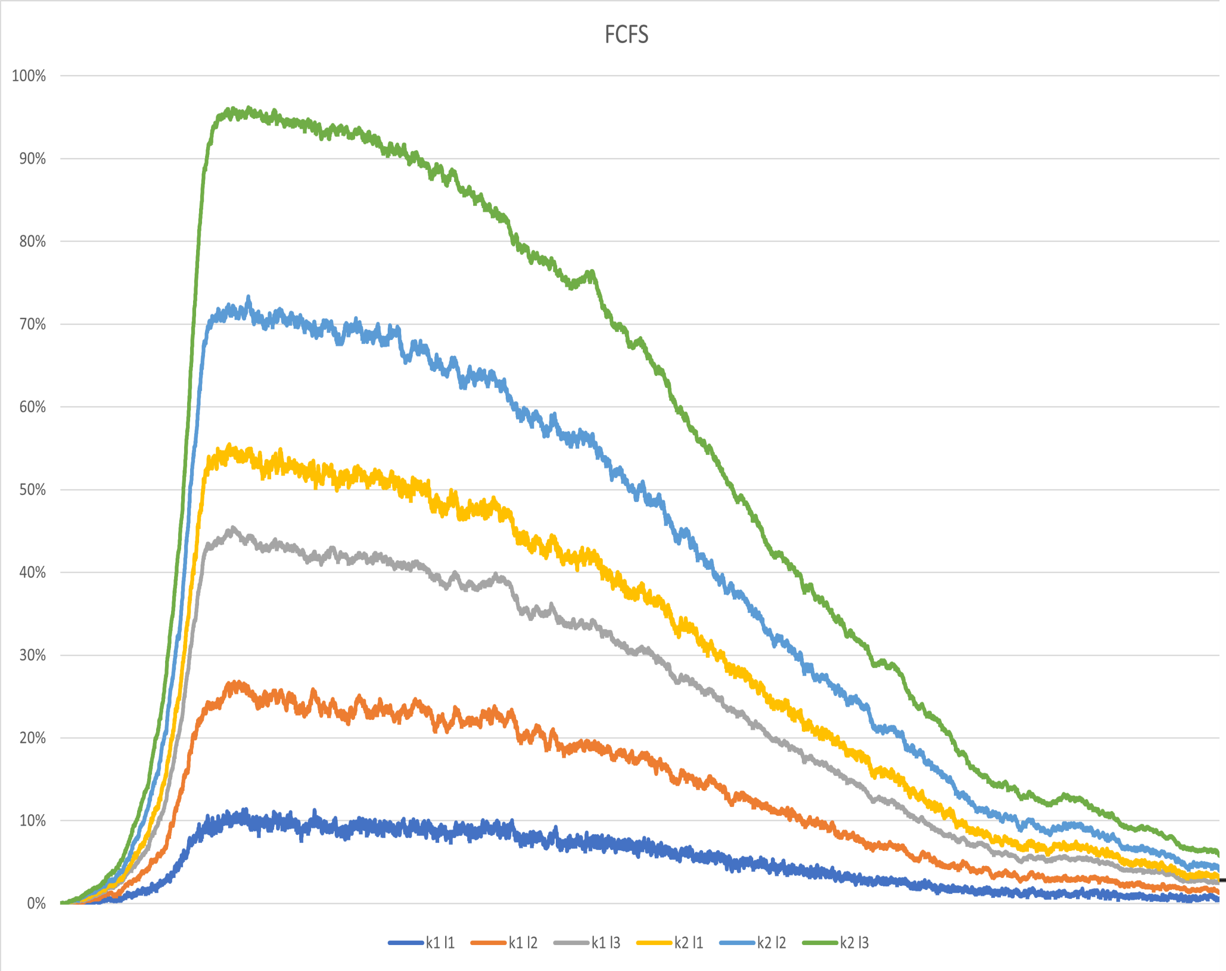
Total expected arrivals: 185 over 365 days
Number of ICU beds: 6
Penalty for early discharges: 0.5
Simulation replications: 500

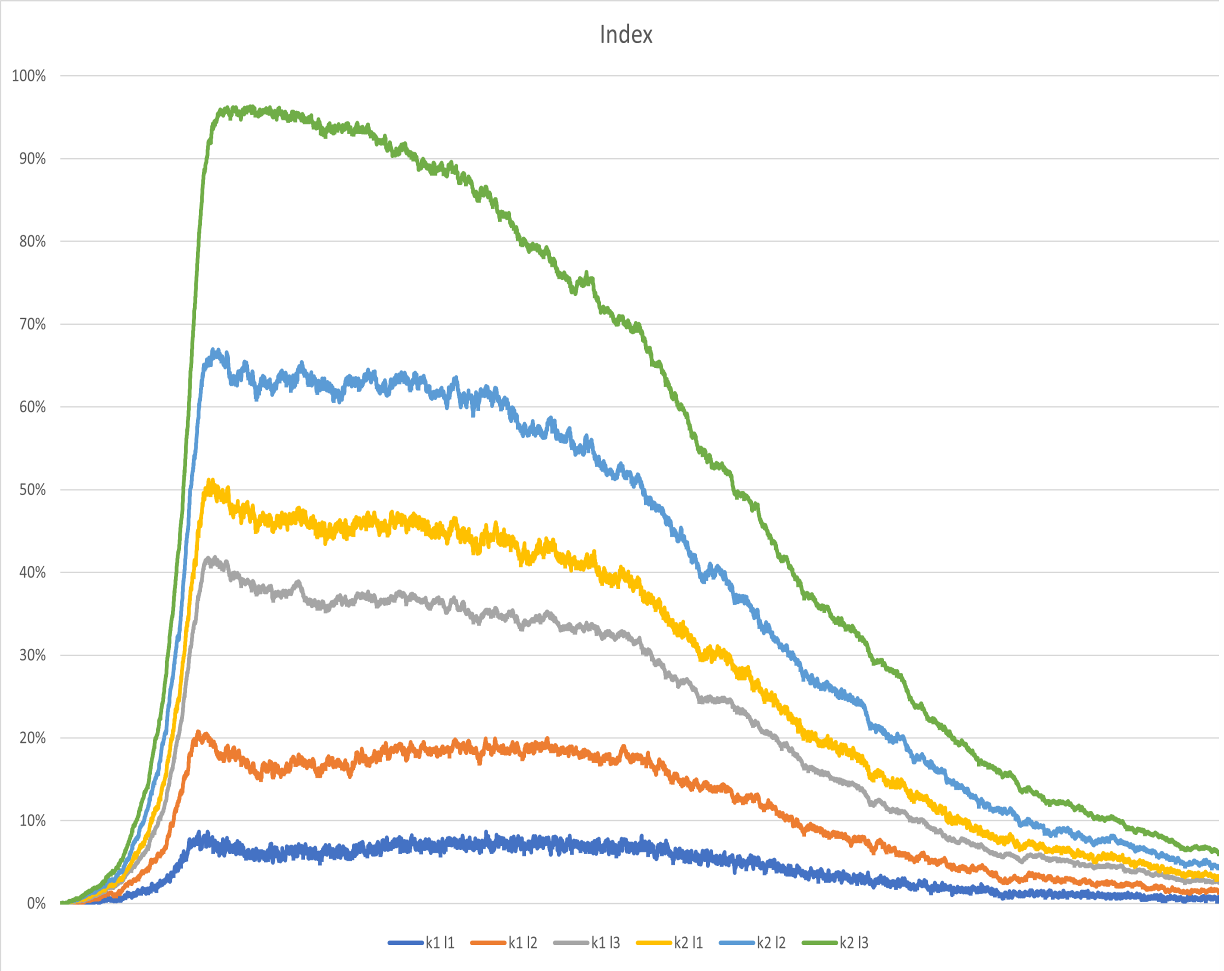
The Key Results

RR=0.63	FCFS	Interrupt	Index
Total death	81	77	78
Below 60	23	23	22
60+	58	54	56
Total admission	90	140	115
Below 60	43	58	53
60+	47	82	62
Total early discharges	0	54	28
Below 60	0	30	16
60+	0	24	12
early dischasrge rate (overall)	0%	39%	24%
Life-years lost	1766	1710	1718

RR=0.4	FCFS	Interrupt	Index
Total death	101	99	103
Below 60	31	26	24
60+	70	73	79
Total admission	90	153	126
Below 60	43	81	70
60+	47	73	56
Total early discharges	0	64	35
Below 60	0	27	6
60+	0	37	29
early dischasrge rate (overall)	0%	42%	28%
Life-years lost	2263	2137	2178

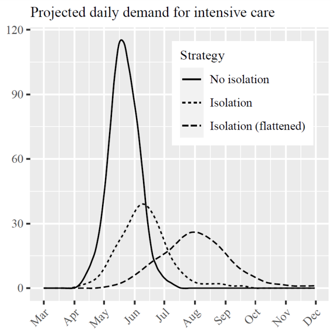
Bed Occupancy FCFS vs Index (RR=0.63)





Simulation scenarios

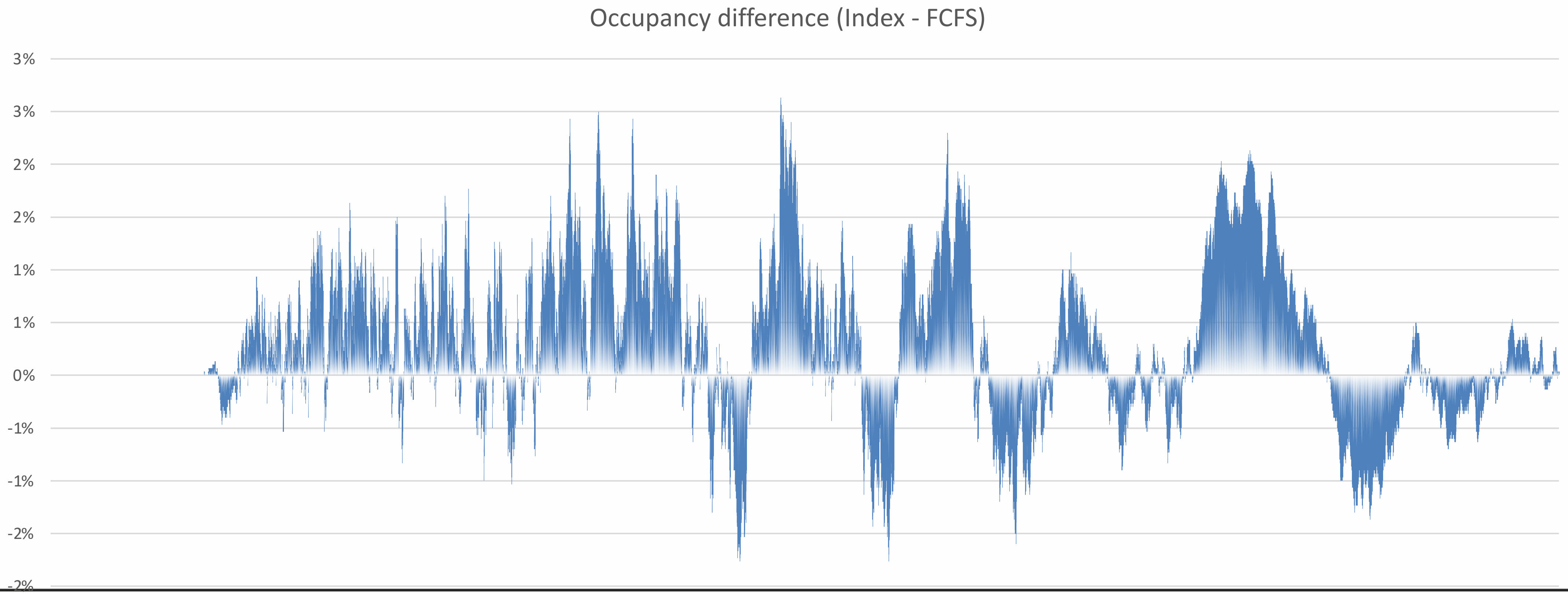
Scenario	Demand profile	Capacity (intensive care beds)	Mean length of stay (days)
1	No isolation	45	8.07
2	Isolation	45	8.07
3	Isolation	76	8.07
4	Isolation	100	8.07
5	Isolation	45	6.05
6	Isolation	45	10.09
7	Isolation (flattened)	45	8.07
8	Isolation (flattened)	76	8.07
9	Isolation (flattened)	100	8.07
10	Isolation (flattened)	100	6.05



baseline = 45 beds
first surge = 76 beds
second surge 100 beds

baseline = 8.07 days
-25% = 6.05 days
+25% = 10.09 days

Bed Occupancy FCFS vs Index (RR=0.63)



The Takeaways

- *FCFS* leads to highest lives and/or life-years lost
- *Interrupt* strategy leads to the least losses, but at the expense of a lot of early discharges
- Index policy strikes a balance in earlier discharges between Interrupt and FCFS, fine-tuned by the early discharge penalty.
  - If the early discharge penalty = Very large, index becomes FCFS
  - If the early discharge penalty = 0, index becomes close to interrupt
- AS RR decreases (i.e., risk increases by not admitting patients to ICU), more younger deaths can be avoided by applying index policy.
- Bed occupancy between FCFS and Index
  - Index policy leads to higher bed occupancy over time
  - More beds are occupied by higher severity level patients under index policy

Thank you !

And happy to take any questions!