Citation for published version:
Wood, R, Pratt, A, Kenward, C, McWilliams, C, Booton, R, Thomas, MJ, Bourdeaux, C & Vasilakis, C 2021, 'The value of triage during periods of intense COVID-19 demand: simulation modelling study', *Medical Decision Making*. https://doi.org/10.1177/0272989X21994035

DOI:
10.1177/0272989X21994035

Publication date:
2021

Document Version
Peer reviewed version

Link to publication

IN PRESS AT *MEDICAL DECISION MAKING* (ACCEPTED 15 JANUARY 2021)

The value of triage during periods of intense COVID-19 demand: simulation modelling study

Richard M Wood Ph.D.[1,2,7], Adrian C Pratt Ph.D.[1], Charlie Kenward MB ChB[3], Christopher J McWilliams Ph.D.[4], Ross D Booton Ph.D.[5], Matthew J Thomas MB ChB[6], Christopher P Bourdeaux MB BChir[6], Christos Vasilakis Ph.D.[2]

[1] Modelling and Analytics; UK National Health Service (BNSSG CCG); UK.
[2] Centre for Healthcare Innovation and Improvement (CHI[2]); School of Management; University of Bath; UK.
[3] Clinical Effectiveness; UK National Health Service (BNSSG CCG); UK.
[4] Department of Engineering Mathematics; University of Bristol; UK.
[5] Bristol Veterinary School; University of Bristol; UK.
[6] Intensive Care Medicine; Bristol Medical School; University of Bristol; UK.
[7] Corresponding author. South Plaza; Marlborough St; Bristol; BS1 3NX; UK. richard.wood16@nhs.net.

Abstract

Background During the COVID-19 pandemic many intensive care units have been overwhelmed by unprecedented levels of demand. Notwithstanding ethical considerations, the prioritisation of patients with better prognoses may support a more effective use of available capacity in maximising aggregate outcomes. This has prompted various proposed triage criteria, although in none of these has an objective assessment been made in terms of impact on number of lives and life-years saved.

Design An open source computer simulation model was constructed for approximating the intensive care admission and discharge dynamics under triage. The model was calibrated from observational data for 9505 patient admissions to UK intensive care units. In order to explore triage efficacy under various conditions, scenario analysis was performed using a range of demand trajectories corresponding to differing non-pharmaceutical interventions.

Results Triaging patients at the point of expressed demand had negligible effect on deaths but reduces life-years lost by up to 8.4% (95% CI: 2.6% to 18.7%). Greater value may be possible through ‘reverse triage’, i.e. promptly discharging any patient not meeting the criteria if admission cannot otherwise be guaranteed for one that does. Under such policy, life-years lost can be reduced by 11.7% (2.8% to 25.8%), which represents 23.0% (5.4% to 50.1%) of what is operationally feasible with no limit on capacity and in absence of improved clinical treatments.

Conclusions The effect of simple triage is limited by a trade-off between reduced deaths within intensive care (due to improved outcomes) and increased deaths resulting from declined admission (due to lower throughput given the longer lengths of stay of survivors). Improvements can be found through reverse triage, at the expense of potentially complex ethical considerations.

Keywords Triage; Intensive Care; Critical Care; COVID-19; Coronavirus; Computer Simulation

1. Introduction

COVID-19 is a virulent disease caused by the highly contagious Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2). With an *R0,* or basic reproduction number, estimated as high as 6.5 it has proliferated globally and was declared a pandemic by the World Health Organisation on 12th March 2020 [1]. It poses a particular concern to public health and healthcare authorities due to the potential severity of resulting symptoms, with an estimated 15% of symptomatic UK cases requiring hospital admission [2]. The complexity of these symptoms is such that a small but significant proportion (17%) of hospitalised patients require transfer to intensive care [2], of which 41% eventually die within intensive care [3]. This can, and has, put a strain on the healthcare services of even the most developed nations with demand for intensive care, and in particular the administration of mechanical ventilation, exceeding available supply [4, 5].

The fundamental concept of prioritisation is that restricting access to those for whom admission is not likely or expected to significantly improve survival outcomes increases the availability of beds for those with greater potential to benefit [6]. This *triaging* of intensive care is not a novel consideration [7, 8] and has been driven in part by longstanding findings such as 38% of intensive care resources being consumed by the 15% of patients who die [9]. Yet while triage offers an opportunity to improve aggregate outcomes, it is not without some ethical dilemma since those patients whose admission is declined may have negligible probability of survival [10, 11].

Regarding the particularly severe pressure put on intensive care resources during a pandemic, the research interest in triage strategy intensified following the outbreaks of SARS-CoV-1 (SARS) and H5N1 (avian flu). In an influential paper, Christian et al [12] proposed an influenza pandemic triage protocol which firstly checks candidacy through predefined criteria, with those deemed suitable thereafter prioritised based upon the extent of organ failure (as measured by Sequential Organ Failure Assessment score, i.e. SOFA score). Building upon the prioritisation concept of this protocol, Frolic et al [13] addressed their concerns regarding the sensitivity of the SOFA score through additional prioritisation criteria arising from the ‘fair-innings’ principle that “*all people should have the opportunity to live through all stages of life*” (the example they use being that a 20-year-old may be prioritised over a 60-year-old who has had 40 more years of life experience). Age was also found to have support as a pandemic triage factor following a survey of 550 intensive care clinicians [14]. This led to a modified set of exclusion criteria which accounted for patients with an age of 85 years or above. Other points-based prioritisation approaches for use in an influenza pandemic have incorporated age, with 60 years used as a threshold [15, 16].

In relation to COVID-19, patient age has already been used as a basis for intensive care triage decisions [10, 17]. Age has also featured in various published guidelines regarding the use of triage, given it is a key determinant of intensive care survival chances [3, 4] and that priority should be given to those with “*the highest probability to benefit*” [18]. As well as triaging based on short-term outcomes, several investigators advocate that longer-term survival factors should also be taken into account. Referring to life-years saved, White & Lo [10] suggest that “*younger individuals should receive priority [since] they have had the least opportunity to live through life’s stages*” (i.e. the afore-mentioned ‘fair-innings’ principle). This is supported by the recommendations of Emanuel et al [19], who additionally suggest that coexisting conditions should be factored in to estimations of life expectancy alongside age, i.e. in the words of Sprung et al [20] it is the “*importance of physiological not chronologic age*”. Knowing in what measures to balance short and long term survival is not a decision that has reached consensus. Pre pandemic, Biddison et al [16] have found some support for the former, while maximisation of life-years is targeted through the triage decision support algorithm proposed by Sprung et al [17].

Guidelines for triaging COVID-19 demand must also confront the issue of whether patients may remain in intensive care until an otherwise natural conclusion is reached, or whether they may be prematurely discharged in order to admit those with more favourable chances. In addressing this, Hope et al [21] recommend that “*priority should be independent of whether patients are already* *receiving intensive care*". Guidelines specific to COVID-19 appear to support this principle [17, 19, 22], in part justified through the consideration of each admission as an "*ICU trial*" [23] and not an "*unlimited promise*" [10]. There are ethical and moral concerns associated with the early discharging of patients, as well as triage policies more generally, and the reader may refer to [23, 24] for a discussion of these in the COVID-19 context.

A more quantitative perspective into the differential benefit of triage strategies is possible through Operational Research methods such as queuing theory and discrete event simulation. These involve constructing a dynamical mathematical or computer simulation model of the arrival, admission and discharge processes with the aim of facilitating the examination of hypothetical 'what if' scenarios involving changes to the various levers at the control of clinicians and hospital managers. Yet, while there is a plethora of examples of such methods applied to intensive care settings [25-27], very few studies have considered triage strategies potentially necessary for pandemics such as COVID-19. One exception is the modelling study by Utley et al [28] that sought to explore the underlying mechanisms associated with triage and whether these could lead to fewer deaths in a patient population in need of critical care during a pandemic. Notwithstanding practical limitations, since the authors "*made no attempt to define clinical triage criteria*" and did not consider long-term survival (e.g. through life-years), the conclusion is made that triage cannot be assumed to result in fewer deaths and that its impact is disease specific. Albeit with no new modelling, the authors of this study have relayed their concerns within the COVID-19 context, suggesting that health services "*urgently needs to address the question of how access to intensive care is determined when there are not sufficient resources to treat everyone*" [29].

The purpose of this study is to investigate the likely impact of various strategies for triaging admission to intensive care during the COVID-19 pandemic. The primary outcome measures are aggregate lives and life-years saved relative to the baseline involving no triage (where patients are admitted on a first-come, first-served basis). The remainder of this paper is structured as follows. In Section 2 the computer simulation model is detailed alongside a description of its calibration and the scenarios considered. Section 3 presents the results of the modelling, with Section 4 containing a discussion of limitations, practical considerations and further work.

2. Methods

2.1 Model

Discrete event simulation was used to model the intensive care arrival, admission and discharge dynamics. This is a conceptually appropriate technique for representing the distinct types of activity associated with patient flow, as demonstrated by its established history of use in the healthcare setting [30, 31], including intensive care, for which a review has found simulation to be the most used modelling approach [32]. Specifically, within the COVID-19 context, discrete event simulation is the main suggested method for investigating decisions relating to intensive care capacity [33] and has been used in early efforts, albeit without consideration to triage [34, 35].

The model used here is based upon the approach developed by Wood et al [34] for modelling intensive care dynamics in the COVID-19 setting. This involved the modelled consideration of deaths occurring within intensive care and those occurring as a result of declined admission (due to insufficient bed availability). Since patients were assumed homogeneous there was no ability to model triage strategies based upon individuals' attributes. Accordingly, an extension is made here in order to allow for the inclusion of a number of patient groups, definable by the factor(s) on which triage criteria may be based. Correspondingly, further modification is made in augmenting the modelled queue discipline from the originally-assumed 'first-come, first-served' to allow for the three triage strategies outlined in Section 2.2. Supplementary Material A contains full details on the model and its solution. The open source model code is available at [36]. Note that the appropriate guidelines for this type of study have been followed, i.e. Strengthening The Reporting of Empirical Simulation Studies (STRESS) [37].

2.2 Triage strategies

Patient age is used as the sole determinant for simulated triage decisions, given that (a) it has already been used in practice to support triage decisions, (b) it is a credible marker for short and long term survival, and (c) there are, at the time of the study, relevant data available for model calibration. Three triage strategies are investigated against a baseline involving no triage where adult patients of all ages (16 years and over) are admitted on a first-come, first-served basis (Figure 1). The first strategy accounts for a rigid cut-off, in which no patient is admitted to intensive care whose age is above the considered threshold (*Cut-off* strategy). The second strategy relaxes this constraint, to the extent that such patients are admitted provided there is at least a certain number of beds available at the point of demand (*Tolerance* strategy). Under the third strategy – sometimes referred to as 'reverse triage' – patients of all considered ages are admitted (provided there is an available bed) with those of age greater than the considered threshold discharged upon arrival of a younger patient whose admission cannot otherwise be accommodated (*Interrupt* strategy). The three types of death that may result under these strategies are illustrated in Figure 2.

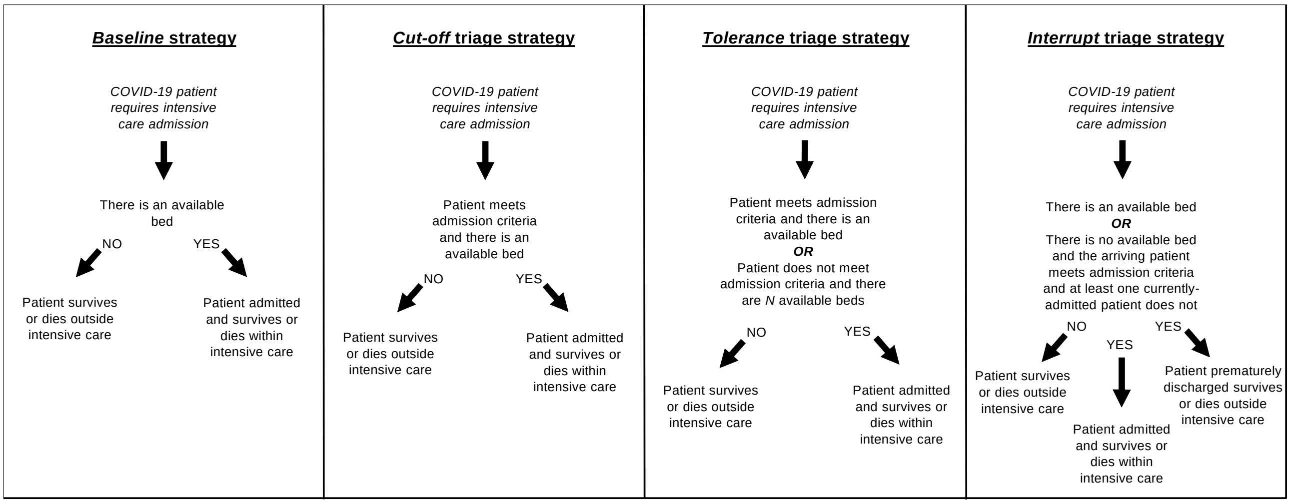

Figure 1. The three triage strategies considered in this study, in addition to the 'first-come, first-served' baseline strategy involving no prioritisation based on patient age.

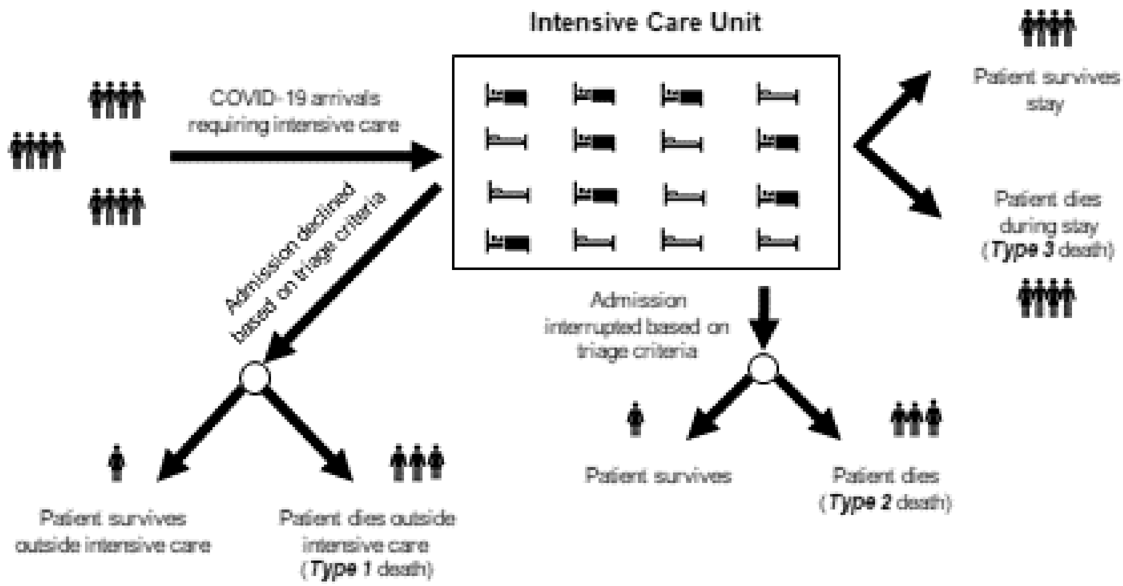

Figure 2. Types of death that may result under the various triage strategies considered in this study.

2.3 Application

Activities were simulated for a 20-bed intensive care unit under the assumption that each bed had provisions for mechanical ventilation if required. This number of beds was considered reasonable for a typical intensive care unit, based on surveys from the UK and US [38-40]. In order to gauge sensitivity to different ward sizes, modelling was also performed on ward sizes ranging from 10 to 200 beds.

Demand for intensive care admission was generated using a *Susceptible-Exposed-Infected-Recovered* (SEIR) compartmental model [41] developed for use within the COVID-19 setting (note this model, summarised in Supplementary Material B, has been in routine use within the authors' healthcare system for forecasting infections and associated bed demand). For this study, three demand trajectories for intensive care admission were synthetically generated with the aim of stressing the bed base sufficiently in order to effectively test the triage criteria (Figure 3). The *Unmitigated* trajectory displays initial exponential growth in demand before increasing herd immunity reduces spread. The long-term use of non-pharmaceutical interventions to limit social contact are accounted for in the *Lockdown* trajectory, resulting in a smaller peak and a longer tail as the population gradually becomes more saturated (i.e. gains infection-acquired immunity). Under the *Cyclical* trajectory, more restrictive measures are assumed but over shorter periods of time, resulting in three 'waves' over the considered period.

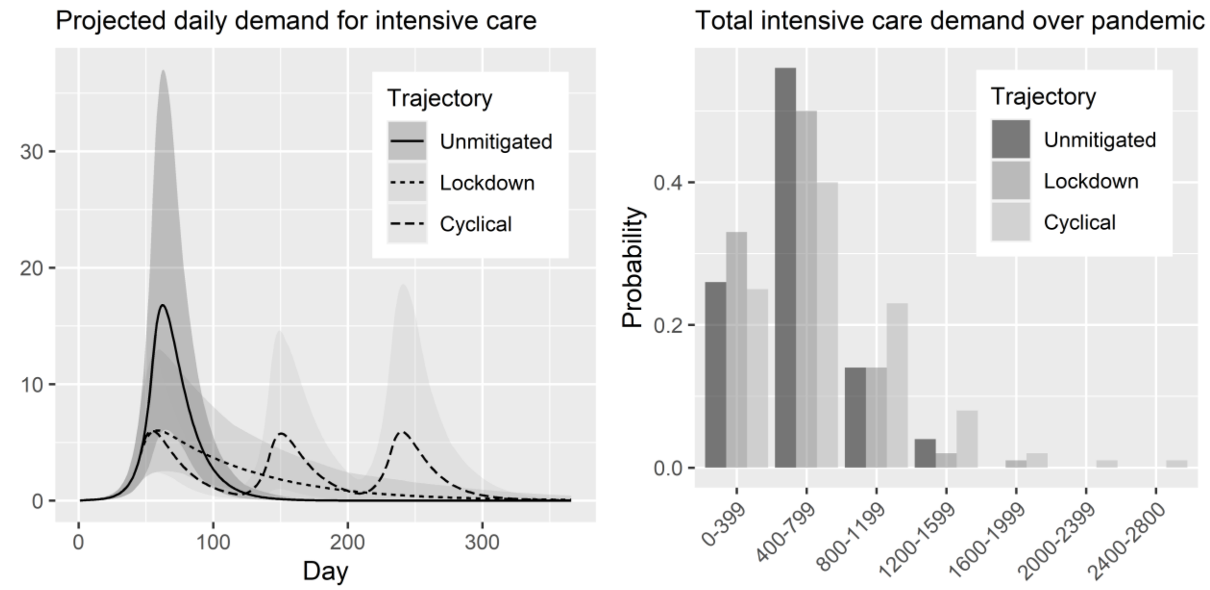

Figure 3. Demand trajectories for numbers requiring intensive care admission and corresponding total numbers requiring intensive care admission over simulated pandemic.

Table 1 contains model inputs at patient group level. Patient groups are defined by the six age brackets provided in the weekly reports published by the Intensive Care National Audit and Research Centre (ICNARC, https://www.icnarc.org), who compile data for COVID-19 related admissions across England, Wales and Northern Ireland (note, hospitals in Scotland have not participated in this data audit). For this study, data from the report published on 26 June 2020 was used [3]. Proportions of admission demand (Figure 3) allocated to each of the patient groups were determined by the volume of admissions (n=9505) correspondent to each age bracket, as obtained through [3]. The probability that a patient will die if not admitted to intensive care was assumed uniform across all patient groups and was set equal to that used in [34], deduced on the basis of clinical guidance and with support from [10, 11]. In absence of available data, it was estimated that the probability of death given interruption (i.e. premature discharge) was equal to this value. The probability that a patient will die within intensive care was sourced from [3]. Life years remaining was calculated as the sex-weighted mean value for each age group using UK national life tables published by the Office for National Statistics [42]. Further explanation is provided in Supplementary Material C.

Table 1. Estimates of model parameters at patient group level.

Patient group	**Proportion of intensive care demand**	**Probability of death if admission declined or interrupted**	**Probability of death within intensive care**	**Life-years remaining**
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

Table 2 details the parameter values relating to intensive care length of stay. These were deduced from outcome level figures for median and inter-quartile range as presented within [3]. For survivals, the median length of stay was 12 days (IQR 5, 26), and for deaths it was 9 days (IQR 5, 16). To approximate the underlying distribution of lengths of stay, a parametric distribution was fitted to these quartiles by Matching Quantiles Estimation (MQE), i.e. optimising the distribution parameters such that squared distance between the empirical and fitted quantiles is minimised. This is consistent with the approach used in [34], using a gamma distribution as suggested by Deasy et al [43].

Table 2. Intensive care length of stay parameters at admission outcome level, under the shape-rate parameterisation of the Gamma distribution. Suitability of the fitted distributions are assessed through comparing the fitted and empirical length of stay distribution quartiles (i.e. those reported in [3]).

Admission outcome	**Distribution**	**Parameters**		**Quartiles in days, fitted (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)

A summary of the provenance of data and information used for calibrating all such model parameters is provided in Table 3. As discussed further in Section 4.2, this information should be considered when interpreting the results of this study for particular geographies or periods of time.

Table 3. Summarised provenance of data and information used for calibrating model parameters.

Model parameter	**Value**	**Geography**	**Time period**	**Source**
Intensive care capacity	20 beds (range 10-200)	UK/US	2012-2020	[38-40]
Admission demand trajectories	Figure 3	UK	N/A	[41]
Probability of death if admission declined or interrupted	0.99	UK	2020	[34]
Proportion of intensive care demand per age group	Table 1	UK	1 March to 25 June 2020	[3]
Probability of death within intensive care	Table 1	UK	1 March to 25 June 2020	[3]
Life-years remaining	Table 1	UK	2017-2019	[42]
Length of stay by admission outcome	Table 2	UK	1 March to 25 June 2020	[3]

3. Results

Time-aggregated results for deaths and life-years lost are provided in Table 3 for the full range of considered demand trajectories, triage strategies and age thresholds. As can be seen, prioritisation of intensive care admission by any combination of triage strategy and age threshold does not produce a discernible reduction in total deaths incurred over the course of the simulated pandemic when compared to the baseline (i.e. ‘first-come, first-served’). Indeed, for none of the considered scenarios is a mean reduction in total deaths of more than 3% recorded (Figure 4).

The worst-performing triage strategy in terms of total deaths is that where patients are declined admission if their age is above the considered threshold (*Cut-off* strategy). Rather than save lives, this strategy is shown to result in additional deaths, and to a considerable extent (up to 14%) with a threshold of 50 years. Granting admission to patients over the considered age threshold provided a certain number of beds are free at the point of demand does yield a reduction in deaths (*Tolerance* strategy). Here, more favourable results are obtained for when this tolerance is relaxed to three beds from six, and with an age threshold at 60 years (up to 1.2% deaths can be saved). Of all the considered triage strategies, the best-performing is the one in which all patients are admitted if there is a free bed, with service interrupted for those above the age threshold upon arrival of a patient below the threshold (*Interrupt* strategy). Under this strategy, reductions in total deaths by up to 2.7% (95% CI: 1.5% to 4.0%) are possible with the age threshold set at 60 years.

To understand why the reduction in total deaths is so limited, it is necessary to inspect the composition of deaths by type (Table 4 and Figure 5). Deaths occurring as a result of declined admission (Type 1 deaths) increased relative to the baseline under *Cut-off* and *Tolerance* triage strategies, with opposite movement (decrease) in deaths occurring within intensive care (Type 3 deaths). This is in line with expectation since such triage strategies are restricting the numbers admitted (i.e. more Type 1 deaths) in order to retain available capacity for those more likely to benefit from admission (Type 3 deaths). This is evident from Figure 6 where substantially fewer (27%) patients were admitted under the *Cut-off* strategy compared to the baseline, resulting in lower bed occupancy and a greater number (21%) of Type 1 deaths. Further, the throughput of the intensive care unit is dependent on case-mix: admitting a greater number of younger patients leads to more patients surviving to discharge (Table 1), but at the expense of longer lengths of stay (Table 2) and thus lower throughput. Therefore, the inability of triage to substantially reduce total deaths is due to the balancing of the *positive effects* associated with higher admissions of younger patients (fewer Type 3 deaths) and the corresponding *negative effects* in the form of reduced throughput and lower occupancy levels required to support the admission of younger patients (greater Type 3 deaths).

While a balancing in types of death is also evident under the *Interrupt* triage strategy – albeit consistently in favour of a net reduction relative to baseline (Table 4) – there are marked differences in the dynamics at play. With a greater number of patients admitted than under the *Cut-off* or *Tolerance* strategies (Figure 6), there were fewer (not more) Type 1 deaths relative to the baseline. With approximately equivalent reductions in Type 3 deaths relative to the baseline, the trade-off is between (reduced) Type 1 deaths and (increased) Type 2 deaths. A difference is that, under this triage strategy, these latter deaths are composed entirely of patients above the age threshold (Figure 6). Thus, in addition to the modest reductions in total deaths, a greater improvement to the number of life-years lost would be expected.

Life-years lost, unlike deaths, is reduced relative to the baseline across all considered scenarios, with the exception of *Cut-off* for the *Lockdown* and *Cyclical* demand trajectories under a 50 year threshold (Table 4). This supports the finding that in balancing deaths of different type, such triage is effectively trading-off the lives of older patients for those of a younger age. There are a number of parallels between the results for life-years lost and those for deaths. First, the greatest reductions are achieved through the *Interrupt* triage strategy, which yields up to a 11.7% mean reduction in life-years lost for the *Lockdown* and *Cyclical* demand trajectories (Figure 4). Second, any additional benefit of triage is eliminated as the age threshold approaches 80 years. And third, when intensive care is truly overwhelmed in a short space of time, i.e. through the *Unmitigated* demand trajectory, the benefit of triage lessens. This is explained by simply considering each bed as a resource for saving a certain amount of life-years per unit time. If the demand for such resource is concentrated over a smaller window of time, then there is insufficient ability for that resource to be making a difference when needed, yet excessive opportunity when not needed. Spreading demand over a larger period of time enables greater utilisation of the resource, and thus a greater number of life-years that can be saved.

Finally, given the ability of hospitals to increase the number of intensive care beds during a pandemic [4, 23, 44], the effect of capacity on deaths and life-years lost can be assessed (Figure 7). As capacity increases, so any benefits of triage reduce, to the point at which all deaths occur within intensive care (Type 3) and are otherwise unavoidable (in the absence of improved treatment). The rate at which deaths converge to this level is dependent on the extent to which demand exceeds supply – note, for instance, the slower rate of convergence for the more severe *Unmitigated* trajectory. Full results for all scenarios evaluated over these capacities are available at [36].

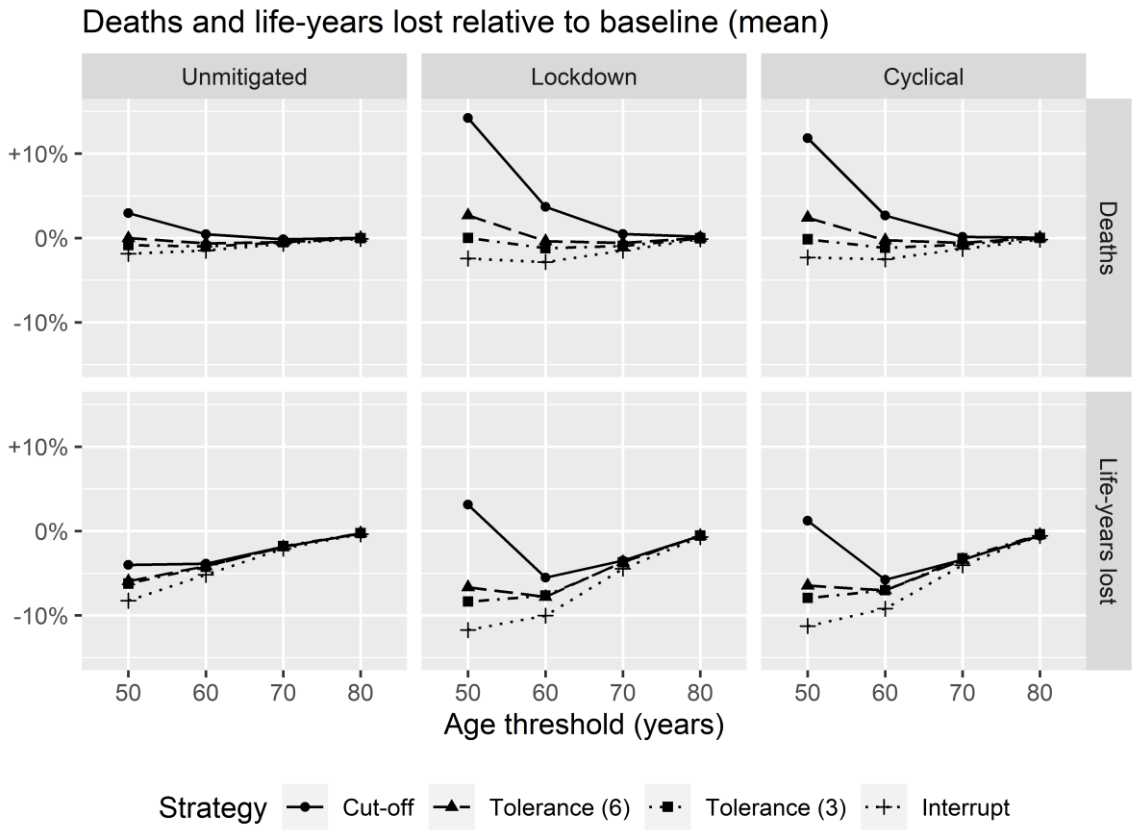

Figure 4. Estimated numbers of deaths and life-years lost by triage strategy. Results are relative to baseline (no triage strategy).

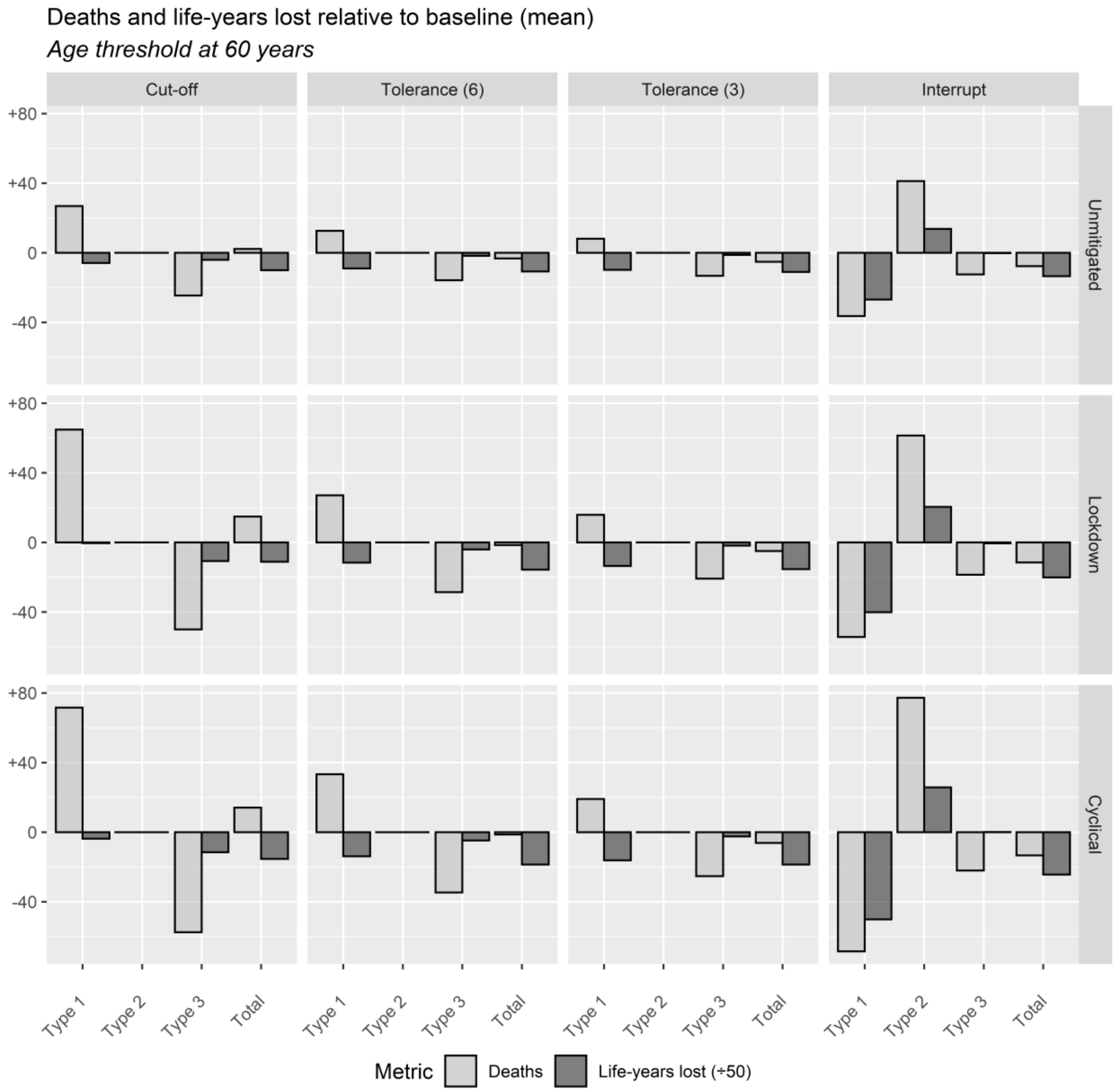

Figure 5. Estimated number and type of death relative to baseline. Results provided for triage strategies with an age threshold of 60 years. Note that Type 1 deaths are those resulting from declined admission, Type 2 deaths are those resulting from interrupted admission, and Type 3 deaths are those occurring during admission (see Figure 2).

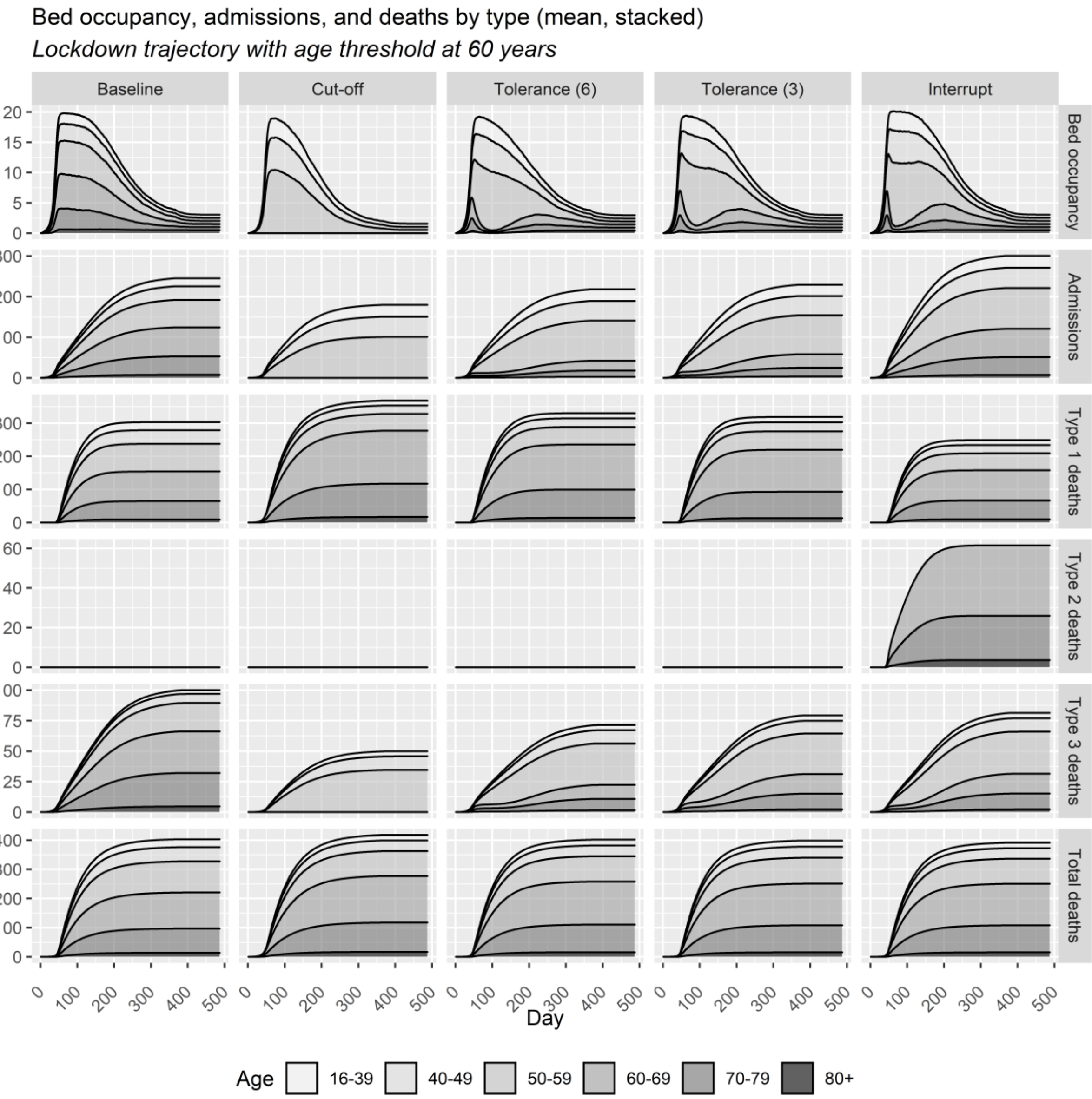

Figure 6. Estimated intensive care bed occupancy and cumulative admissions and deaths over the course of the simulated pandemic. Results provided under the *Lockdown* demand trajectory for triage strategies with an age threshold of 60 years.

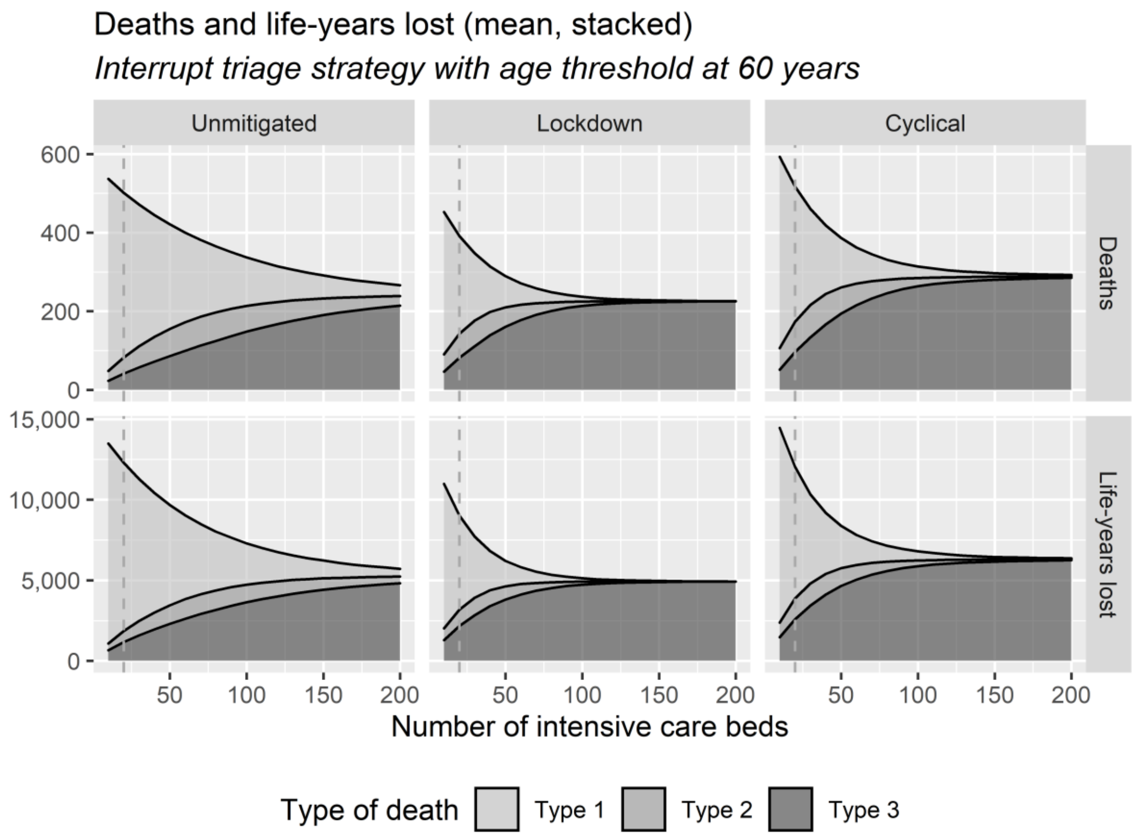

Figure 7. Estimated numbers of deaths and life-years lost for various levels of intensive care capacity. Results provided under the *Interrupt* triage strategy with an age threshold of 60 years.

Table 4. Estimated number of deaths and life-years lost (mean and 95% confidence intervals) over the course of the pandemic according to the range of demand trajectories and triage strategies under consideration. Results present the relative differences from baseline involving no triage strategy (i.e. 'first-come, first-served'), for which actual numbers are provided. Note that Type 1 deaths are those resulting from declined admission, Type 2 deaths are those resulting from interrupted admission, and Type 3 deaths are those occurring during admission (see Figure 2). Note also that for the *Tolerance* strategy the tolerance level, in terms of number of available beds, is provided in parentheses (see Figure 1 for more information).

Demand trajectory	**Triage strategy**	**Threshold (years)**	**Deaths relative to baseline**				**Life-years lost relative to baseline**
			Type 1	**Type 2**	**Type 3**	**Total**	
Unmitigated	***Baseline***	-	***455 (131 to 1178)***	***0 (0 to 0)***	***54 (37 to 75)***	***509 (180 to 1237)***	***12968 (4504 to 31634)***
Unmitigated	Cut-off	50	+54 (49 to 61)	0 (0 to 0)	-39 (-50 to -30)	+15 (9 to 24)	-521 (-763 to -21)
Unmitigated	Cut-off	60	+27 (23 to 27)	0 (0 to 0)	-25 (-33 to -20)	+2 (-9 to 5)	-501 (-761 to -483)
Unmitigated	Cut-off	70	+10 (8 to 9)	0 (0 to 0)	-11 (-14 to -9)	-1 (-5 to 2)	-240 (-316 to -303)
Unmitigated	Cut-off	80	+2 (0 to 5)	0 (0 to 0)	-2 (-3 to -2)	+0 (-3 to -2)	-41 (-229 to 6)
Unmitigated	Tolerance (6)	50	+22 (22 to 24)	0 (0 to 0)	-22 (-30 to -16)	0 (-4 to 7)	-770 (-1178 to -469)
Unmitigated	Tolerance (6)	60	+13 (13 to 13)	0 (0 to 0)	-16 (-22 to -12)	-3 (-8 to 0)	-540 (-641 to -436)
Unmitigated	Tolerance (6)	70	+5 (-4 to 2)	0 (0 to 0)	-8 (-11 to -7)	-3 (-6 to -5)	-247 (-506 to -290)
Unmitigated	Tolerance (6)	80	+1 (1 to 3)	0 (0 to 0)	-1 (-3 to -1)	+0 (0 to 0)	-34 (-59 to 136)
Unmitigated	Tolerance (3)	50	+13 (10 to 11)	0 (0 to 0)	-17 (-23 to -14)	-4 (-7 to 3)	-808 (-1076 to -434)
Unmitigated	Tolerance (3)	60	+8 (7 to 14)	0 (0 to 0)	-13 (-18 to -10)	-5 (-5 to -2)	-551 (-581 to -572)
Unmitigated	Tolerance (3)	70	+4 (3 to 4)	0 (0 to 0)	-6 (-9 to -5)	-3 (0 to 1)	-233 (-254 to -247)
Unmitigated	Tolerance (3)	80	+1 (1 to 2)	0 (0 to 0)	-1 (-3 to -1)	0 (-2 to 1)	-32 (-55 to 127)
Unmitigated	Interrupt	50	-43 (-58 to -32)	+50 (26 to 71)	-16 (-22 to -12)	-10 (-16 to -7)	-1070 (-1516 to -708)
Unmitigated	Interrupt	60	-36 (-48 to -35)	+41 (26 to 58)	-12 (-17 to -10)	-8 (-8 to -7)	-673 (-822 to -614)
Unmitigated	Interrupt	70	-17 (-24 to -18)	+20 (11 to 30)	-6 (-10 to -4)	-3 (-3 to -2)	-270 (-494 to -242)
Unmitigated	Interrupt	80	-2 (-4 to -1)	+3 (0 to 7)	-1 (-4 to -1)	0 (-2 to 1)	-48 (-227 to 90)
Lockdown	***Baseline***	-	***303 (49 to 888)***	***0 (0 to 0)***	***100 (54 to 158)***	***403 (116 to 1014)***	***10033 (2751 to 25817)***
Lockdown	Cut-off	50	+136 (113 to 137)	0 (0 to 0)	-79 (-116 to -48)	+57 (44 to 55)	+316 (-848 to 988)
Lockdown	Cut-off	60	+65 (59 to 63)	0 (0 to 0)	-50 (-73 to -31)	+15 (10 to 21)	-555 (-1323 to 13)
Lockdown	Cut-off	70	+23 (18 to 24)	0 (0 to 0)	-21 (-30 to -15)	+2 (-1 to 6)	-351 (-725 to -113)
Lockdown	Cut-off	80	+3 (5 to 23)	0 (0 to 0)	-3 (-3 to -1)	+1 (3 to 12)	-57 (-26 to 22)
Lockdown	Tolerance (6)	50	+47 (38 to 51)	0 (0 to 0)	-36 (-62 to -17)	+11 (-1 to 14)	-667 (-2201 to 45)
Lockdown	Tolerance (6)	60	+27 (22 to 26)	0 (0 to 0)	-29 (-51 to -14)	-2 (-3 to 8)	-783 (-1343 to -195)
Lockdown	Tolerance (6)	70	+11 (11 to 13)	0 (0 to 0)	-13 (-22 to -6)	-2 (0 to 3)	-369 (-338 to -156)
Lockdown	Tolerance (6)	80	+1 (2 to 4)	0 (0 to 0)	-1 (-4 to 0)	+0 (-1 to 4)	-57 (-50 to 59)
Lockdown	Tolerance (3)	50	+24 (15 to 36)	0 (0 to 0)	-24 (-42 to -9)	+0 (-6 to 1)	-839 (-1869 to -261)
Lockdown	Tolerance (3)	60	+16 (12 to 21)	0 (0 to 0)	-21 (-38 to -11)	-5 (-11 to 3)	-768 (-1310 to -237)
Lockdown	Tolerance (3)	70	+7 (2 to 7)	0 (0 to 0)	-10 (-18 to -6)	-4 (-7 to -1)	-373 (-485 to -319)
Lockdown	Tolerance (3)	80	+1 (1 to 1)	0 (0 to 0)	-1 (-5 to 0)	0 (0 to 5)	-54 (1 to 67)
Lockdown	Interrupt	50	-49 (-100 to -13)	+55 (9 to 123)	-16 (-30 to -5)	-10 (-22 to 0)	-1177 (-2591 to -278)
Lockdown	Interrupt	60	-54 (-84 to -27)	+61 (21 to 117)	-19 (-33 to -10)	-11 (-16 to -6)	-1006 (-1613 to -470)
Lockdown	Interrupt	70	-29 (-42 to -16)	+32 (12 to 60)	-9 (-17 to -5)	-6 (-8 to -1)	-447 (-599 to -199)
Lockdown	Interrupt	80	-4 (-5 to -1)	+5 (1 to 11)	-1 (-2 to 0)	-1 (-2 to 1)	-71 (-197 to -33)
Cyclical	***Baseline***	-	***412 (39 to 1276)***	***0 (0 to 0)***	***118 (54 to 167)***	***531 (101 to 1435)***	***13264 (2362 to 36507)***
Cyclical	Cut-off	50	+155 (104 to 136)	0 (0 to 0)	-92 (-115 to -48)	+63 (22 to 52)	+163 (-2339 to 996)
Cyclical	Cut-off	60	+72 (58 to 60)	0 (0 to 0)	-58 (-69 to -33)	+14 (-5 to 21)	-768 (-1843 to 86)
Cyclical	Cut-off	70	+25 (22 to 35)	0 (0 to 0)	-24 (-29 to -14)	+1 (-2 to 7)	-451 (-640 to -36)
Cyclical	Cut-off	80	+3 (0 to 6)	0 (0 to 0)	-3 (-5 to -1)	+0 (0 to 1)	-77 (13 to 21)
Cyclical	Tolerance (6)	50	+58 (24 to 78)	0 (0 to 0)	-45 (-69 to -11)	+13 (-10 to 9)	-857 (-3036 to 6)
Cyclical	Tolerance (6)	60	+33 (16 to 50)	0 (0 to 0)	-35 (-52 to -9)	-1 (-16 to 4)	-931 (-1938 to -89)
Cyclical	Tolerance (6)	70	+13 (3 to 13)	0 (0 to 0)	-16 (-25 to -4)	-3 (-12 to 0)	-452 (-809 to -84)
Cyclical	Tolerance (6)	80	+2 (-1 to 12)	0 (0 to 0)	-2 (-3 to 1)	+0 (0 to 4)	-59 (-39 to 151)
Cyclical	Tolerance (3)	50	+29 (8 to 43)	0 (0 to 0)	-30 (-51 to -6)	-1 (-14 to 5)	-1052 (-2940 to -12)
Cyclical	Tolerance (3)	60	+19 (5 to 31)	0 (0 to 0)	-25 (-43 to -6)	-6 (-16 to 1)	-930 (-1956 to -167)
Cyclical	Tolerance (3)	70	+9 (2 to 13)	0 (0 to 0)	-13 (-24 to -3)	-4 (-1 to 0)	-428 (-731 to -24)
Cyclical	Tolerance (3)	80	+2 (-1 to 7)	0 (0 to 0)	-2 (-3 to 1)	0 (1 to 4)	-53 (-37 to 126)
Cyclical	Interrupt	50	-64 (-135 to -11)	+72 (6 to 167)	-20 (-37 to -3)	-12 (-26 to -3)	-1493 (-3346 to -177)
Cyclical	Interrupt	60	-69 (-115 to -19)	+77 (15 to 142)	-22 (-39 to -4)	-13 (-21 to -3)	-1220 (-2083 to -281)
Cyclical	Interrupt	70	-35 (-54 to -18)	+40 (9 to 71)	-12 (-19 to -2)	-7 (-3 to -1)	-537 (-812 to -119)
Cyclical	Interrupt	80	-5 (-7 to 12)	+6 (1 to 14)	-2 (-4 to 0)	-1 (0 to 6)	-77 (13 to 25)

4. Discussion

4.1 Key findings and associated ethical considerations

Perhaps the most significant finding of this study has been the relative value of the *Interrupt* triage strategy (sometimes referred to as 'reverse triage'). As well as safeguarding ready access for those with greater survival chances, this policy, through the ability to prematurely discharge patients, actually provides some of those who would otherwise have been declined admission at least some possibility of benefitting from intensive care. This is shown to reduce life-years lost by up to 12% from the 'first-come, first-served' baseline, although the corresponding reduction in deaths is a modest 2.7%. While this can, in part, be explained by lower throughput due to longer lengths of stay associated with the younger patient case-mix (Section 3), there are other factors to consider in interpreting this figure. First, it lacks full context without consideration to the maximum operational improvements possible. Under the *Lockdown* demand trajectory, triage by the *Interrupt* strategy with an age threshold of 60 years yields a mean reduction of 11 deaths compared to the baseline of 403 (Table 4). Yet even with no limitations on capacity there would still be a mean 226 deaths (Figure 7), i.e. the reduction in deaths in terms of that operationally possible is 6.2% (for life-years this extends from a saving of 10.0% to 19.7%). The second factor to note is that, due to a conservative assessment of premature discharge mortality, these figures may be considered lower bounds. It was assumed – in absence of available data – that patients discharged prematurely, at any number of days post-admission, had the same probability of death (0.99) as those declined admission. Realistically, survival chances would be significantly greater if, say, a patient was discharged at 19 days into what otherwise would have been a 20 day admission. The potential scale of realisable opportunity can be gauged through results pertaining to the afore-mentioned scenario, where 16% (61) of the 392 deaths were calculated as Type 2 (Table 4). Note that, for similar reasons, the number of (Type 1) deaths resulting from refused admission may be viewed as an upper bound, given the potential that the assumed 0.99 probability of death could be lesser for younger patients (although appropriate data is not available to effectively quantify this).

Notwithstanding the possible scale of lives and life-years saved, there will always be some ethical dilemma regarding the withdrawal of intensive care support. Assessed against the well-established four principles of medical ethics – autonomy, beneficence, non-maleficence, and justice [45] – the *Interrupt* strategy essentially trades off the first three in favour of the fourth. Perhaps the motivation for doing so should be driven by realisable benefit, i.e. are any ethical complexities in prematurely discharging *X* individuals really worth the saving of *Y* life-years on aggregate? Or perhaps it should be better recognised that a decision to not discharge a patient still represents a decision, and that such decisions should be made only through an objective assessment of aggregate outcomes? Perhaps such objectivity may address any 'sunk cost' effect [46], where potentially futile ongoing support is justified on the basis of resource investments to date, at the expense of the more rational need of external patients not subject to this cognitive bias. In the absence of clear policy or guidance (with some exceptions, e.g. [15]), these are all matters that would benefit from further consideration. So too may be issues regarding triage criteria; while age is a suitable marker of both short and long term survival, other explanatory variables include comorbidity burden [19, 20] and ethnicity [47] – the latter of which would clearly raise ethical issues if used as a triage determinant. Indeed, in their review of triage guidelines, Sprung et al find that "*most statements declared that triage criteria should not be based on race or ethnicity*" [20].

4.2 Limitations and further research

The results of this study have been generated through a particular set of inputs and assumptions, and so care should be taken in generalising the findings beyond this considered setting. Firstly, on grounds of geography, it is important to note that the data-driven aspects of model parameterisation have derived from the UK experience (Table 3). Investigators seeking to meaningfully transfer the results of this study to another geography should consider the extent to which assumptions are aligned (e.g. with respect to lengths of stay). Where substantial differences remain, adapting the open source model code to perform a set of modified simulation experiments may be a consideration [36]. This too holds in considering a further wave, for which there may be different profiles of demand than those considered here (Figure 3) or improved mortality rates and lengths of stay from advances in treatment such as dexamethasone [48]. Note that any reductions in length of stay for those that survive would likely further increase the value of triage: as Toltzis et al put it, "*the identification of patients likely to survive with brief ICU support is necessary to gain greatest advantage in a triage allocation scheme*" [6].

Another limitation relates to possible confounding by any use of triage over the period of time for which calibration data was obtained (i.e. up to 26 June 2020). While, following the first wave of COVID-19 in the UK, the chief executive of the National Health Service has stated "*every coronavirus patient needing hospital care, including ventilation, has been able to receive it*" [49] there is nonetheless a substantially lower proportion of older patients admitted to intensive care [3] than in countries of a comparable demography, e.g. Italy [4]. While this would not affect estimates of the (additional) value of triage in the UK context, care should be taken in interpreting the findings within other countries, giving particular reference to any (explicitly or implicitly) enacted triage policies.

A key assumption of the *Interrupt* strategy has been that a patient may be prematurely discharged at any number of days post admission. Other investigators suggest, however, that "*as COVID-19 patients tend to have longer ICU durations [then] reassessments for remaining in the ICU should occur later, at days 10–14*" [17]. Under normal circumstances, it is reasonable for patients to be given a period of time to evidence response to treatment, and while any cohort-level predictions may be poor there is always the chance of a positive individual-level outcome. Yet in times of intense demand, the longer such opportunities are granted the greater the risk of needing to decline admission to those with better odds of survival. The question returns back to the afore-mentioned four principles of medical ethics and the balance of individual versus distributive justice. Further consideration of this matter may be complemented by an understanding of the scale of impact on aggregate outcomes, which can be estimated through minor modification of the open source model code.

Further research could also explore the modelling of additional or alternative determinants for which triage may be mediated. While patient age is a well-recognised marker of short and long term survival, there are other personal attributes which could improve risk sensitivity – for instance, the presence of comorbidities [19, 20]. However, for the modelling undertaken here, the challenge lay in sourcing the relevant data – at the time of this study, only good quality data in the appropriate format was readily available for patient age [3], and thus a complete model parameterisation based upon comorbidities could not be reliably achieved. It is important to note that the model code is in no way bespoke to age, and is accommodating to any number of patient groups defined by any given criteria. With the appropriate data, further work could use the model to 'validate' the optimality of published triage proposals (Section 1), many of which have been suggested without a robust assessment of impact on lives and life-years saved.

4.3 Conclusions

Deciding who may access scarce intensive care resource at times of intense demand is not straightforward. In seeking to avoid some of the complexity, a policy of 'first-come, first-served' may be observed. Yet, as evidenced here, this can result in a sub-optimal number of lives and life-years lost. In light of COVID-19, this has led many investigators to develop triage protocols based on various patient prioritisation criteria. However, in none of these studies is the recommendation complemented by a reliable estimate of effect on lives and life-years lost. This paper therefore makes an important contribution, in evaluating the effect of various triage strategies on these outcomes through a conceptually appropriate model capturing the key operational dynamics.

While this study will make no clinical guidelines regarding the use of triage, it does provide some evidence to support the following principles within the COVID-19 setting. First, that aggregate life-years lost can be reduced through declining intensive care admission at the point of demand (i.e. ‘simple triage’). Second, that such improvements can be extended, in addition to a decline in aggregate deaths, should ethical justification be found to prematurely withdraw intensive care support (i.e. ‘reverse triage’).

Research data

The datasets generated and/or analysed during the current study are available in the ‘triage-modelling’ repository, https://github.com/nhs-bnssg-analytics/triage-modelling.

Acknowledgements

The authors are grateful to the anonymous reviewers and editorial team whose helpful comments and suggestions have improved the legibility and quality of this article.

Authors' contributions

RW conceived and designed the study, produced the model code, performed the analysis, and generated the outputs. CV and CM contributed to design of the study. AP and RB provided the demand trajectory inputs. CV and CK sourced remaining life-year estimates. CB and MT developed the practical and ethical considerations. All authors contributed to the literature review and interpretation of modelled outputs. RW wrote the manuscript with support from CV, and all authors reviewed and approved the manuscript.

References

[1] Liu Y, Gayle AA, Wilder-Smith A, Rocklöv J. The reproductive number of COVID-19 is higher compared to SARS coronavirus. Journal of travel medicine. 2020 Mar 13. https://doi.org/10.1093/jtm/taaa021

[2] Docherty AB, Harrison EM, Green CA, Hardwick HE, Pius R, Norman L, Holden KA, Read JM, Dondelinger F, Carson G, Merson L. Features of 16,749 hospitalised UK patients with COVID-19 using the ISARIC WHO Clinical Characterisation Protocol. medRxiv. 2020 Jan 1. https://doi.org/10.1101/2020.04.23.20076042

[3] ICNARC, Intensive Care National Audit and Research Centre. ICNARC report on COVID-19 in critical care – 26 June 2020; 2020. https://www.icnarc.org/Our-Audit/Audits/Cmp/Reports

[4] Grasselli G, Zangrillo A, Zanella A, Antonelli M, Cabrini L, Castelli A, Cereda D, Coluccello A, Foti G, Fumagalli R, Iotti G. Baseline characteristics and outcomes of 1591 patients infected with SARS-CoV-2 admitted to ICUs of the Lombardy Region, Italy. Jama. 2020 Apr 28;323(16):1574-81. https://doi.org/10.1001/jama.2020.5394

[5] Beitler JR, Mittel AM, Kallet R, Kacmarek R, Hess D, Branson R, Olson M, Garcia I, Powell B, Wang DS, Hastie J. Ventilator Sharing During an Acute Shortage Caused by the COVID-19 Pandemic. American Journal of Respiratory and Critical Care Medicine. 2020 Jun 9(ja). https://doi.org/10.1164/rccm.202005-1586LE

[6] Toltzis P, Soto-Campos G, Kuhn EM, Hahn R, Kanter RK, Wetzel RC. Evidence-based pediatric outcome predictors to guide the allocation of critical care resources in a mass casualty event. Pediatric Critical Care Medicine| Society of Critical Care Medicine. 2015 Sep 1;16(7):e207-16. https://doi.org/10.1097/PCC.0000000000000481

[7] Bion, J. Rationing intensive care. BMJ: British Medical Journal. 310 (6981); 1995. https://doi.org/10.1136/bmj.310.6981.682

[8] Cheung WK, Myburgh J, Seppelt IM, Parr MJ, Blackwell N, DeMonte S, Gandhi K, Hoyling L, Nair P, Passer M, Reynolds C. A multicentre evaluation of two intensive care unit triage protocols for use in an influenza pandemic. Medical journal of Australia. 2012 Aug;197(3):178-81. https://doi.org/10.5694/mja11.10926

[9] Atkinson S, Mason R, McColl L, Bihari D, Smithies M, Daly K. Identification of futility in intensive care. The Lancet. 1994 Oct 29;344(8931):1203-6. https://doi.org/10.1016/S0140-6736(94)90514-2

[10] White DB, Lo B. A framework for rationing ventilators and critical care beds during the COVID-19 pandemic. Jama. 2020 May 12;323(18):1773-4. https://doi.org/10.1001/jama.2020.5046

[11] Rosenbaum L. Facing Covid-19 in Italy—ethics, logistics, and therapeutics on the epidemic's front line. New England Journal of Medicine. 2020 May 14;382(20):1873-5. https://doi.org/10.1056/NEJMp2005492

[12] Christian MD, Hawryluck L, Wax RS, Cook T, Lazar NM, Herridge MS, Muller MP, Gowans DR, Fortier W, Burkle FM. Development of a triage protocol for critical care during an influenza pandemic. Cmaj. 2006 Nov 21;175(11):1377-81. https://doi.org/10.1503/cmaj.060911

[13] Frolic A, Kata A, Kraus P. Development of a critical care triage protocol for pandemic influenza: integrating ethics, evidence and effectiveness. Healthc Q. 2009;12(4):56-64. https://doi.org/10.12927/hcq.2009.21054

[14] Ashton-Cleary DT, Tillyard AR, Freeman NV. Intensive care admission triage during a pandemic: a survey of the acceptability of triage tools. Journal of the Intensive Care Society. 2011 Jul;12(3):180-6. https://doi.org/10.1177/175114371101200303

[15] Utah Hospital Association. Utah Crisis Standards of Care Guidelines. Version 2, June 2018; 2018. Accessed May 29, 2020. Available from: https://health.utah.gov/wp-content/uploads/Final_Utah_Crisis_Standards_of_Care_011719-1.pdf

[16] Biddison EL, Faden R, Gwon HS, Mareiniss DP, Regenberg AC, Schoch-Spana M, Schwartz J, Toner ES. Too many patients… a framework to guide statewide allocation of scarce mechanical ventilation during disasters. Chest. 2019 Apr 1;155(4):848-54. https://doi.org/10.1016/j.chest.2018.09.025

[17] Sprung CL, Joynt GM, Christian MD, Truog RD, Rello J, Nates JL. Adult ICU Triage During the Coronavirus Disease 2019 Pandemic: Who Will Live and Who Will Die? Recommendations to Improve Survival. Critical care medicine. 2020 May 11. https://doi.org/10.1097/CCM.0000000000004410

[18] Borasio GD, Gamondi C, Obrist M, Jox R. COVID-19: decision making and palliative care. Swiss Medical Weekly. 2020 Mar 24;150(1314). https://doi.org/10.4414/smw.2020.20233

[19] Emanuel EJ, Persad G, Upshur R, Thome B, Parker M, Glickman A, Zhang C, Boyle C, Smith M, Phillips JP. Fair allocation of scarce medical resources in the time of Covid-19. https://doi.org/10.1056/NEJMsb2005114

[20] Sprung CL, Danis M, Iapichino G, Artigas A, Kesecioglu J, Moreno R, Lippert A, Curtis JR, Meale P, Cohen SL, Levy MM. Triage of intensive care patients: identifying agreement and controversy. Intensive care medicine. 2013 Nov 1;39(11):1916-24. https://doi.org/10.1007/s00134-013-3033-6

[21] Hope T, Mcmillan J, Hill E. Intensive care triage: Priority should be independent of whether patients are already receiving intensive care. Bioethics. 2012 Jun;26(5):259-66. https://doi.org/10.1111/j.1467-8519.2010.01852.x

[22] Cameron J, Savulescu J, Wilkinson D. Is withdrawing treatment really more problematic than withholding treatment?. Journal of Medical Ethics. 2020 May 25. http://dx.doi.org/10.1136/medethics-2020-106330

[23] Vergano M, Bertolini G, Giannini A, Gristina GR, Livigni S, Mistraletti G, Riccioni L, Petrini F. Clinical ethics recommendations for the allocation of intensive care treatments in exceptional, resource-limited circumstances: the Italian perspective during the COVID-19 epidemic. https://doi.org/10.1186/s13054-020-02891-w

[24] Farrell TW, Francis L, Brown T, Ferrante LE, Widera E, Rhodes R, Rosen T, Hwang U, Witt LJ, Thothala N, Liu SW. Rationing Limited Health Care Resources in the COVID-19 Era and Beyond: Ethical Considerations Regarding Older Adults. Journal of the American Geriatrics Society. 2020 May 6. https://doi.org/10.1111/jgs.16539

[25] Kim SC, Horowitz I, Young KK, Buckley TA. Analysis of capacity management of the intensive care unit in a hospital. European Journal of Operational Research. 1999 May 16;115(1):36-46. https://doi.org/10.1016/S0377-2217(98)00135-0

[26] Griffiths JD, Jones M, Read MS, Williams JE. A simulation model of bed-occupancy in a critical care unit. Journal of Simulation. 2010 Mar 1;4(1):52-9. https://doi.org/10.1057/jos.2009.22

[27] Mahmoudian-Dehkordi A, Sadat S. Sustaining critical care: using evidence-based simulation to evaluate ICU management policies. Health care management science. 2017 Dec 1;20(4):532-47. https://doi.org/10.1007/s10729-016-9369-z

[28] Utley M, Pagel C, Peters MJ, Petros A, Lister P. Does triage to critical care during a pandemic necessarily result in more survivors?. Critical care medicine. 2011 Jan 1;39(1):179-83. https://doi.org/10.1097/CCM.0b013e3181fa3c3b

[29] Pagel C, Utley M, Ray S. Covid-19: how to triage effectively in a pandemic. BMJ Opinion. 2020.

[30] Mohiuddin S, Busby J, Savović J, Richards A, Northstone K, Hollingworth W, Donovan JL, Vasilakis C. Patient flow within UK emergency departments: a systematic review of the use of computer simulation modelling methods. BMJ open. 2017 May 1;7(5). http://dx.doi.org/10.1136/bmjopen-2016-015007

[31] Zhang X. Application of discrete event simulation in health care: a systematic review. BMC health services research. 2018 Dec;18(1):1-1. https://doi.org/10.1186/s12913-018-3456-4

[32] Bai J, Fügener A, Schoenfelder J, Brunner JO. Operations research in intensive care unit management: a literature review. Health care management science. 2018 Mar 1;21(1):1-24. https://doi.org/10.1007/s10729-016-9375-1

[33] Currie CS, Fowler JW, Kotiadis K, Monks T, Onggo BS, Robertson DA, Tako AA. How simulation modelling can help reduce the impact of COVID-19. Journal of Simulation. 2020 Apr 16:1-5. https://doi.org/10.1080/17477778.2020.1751570

[34] Wood RM, McWilliams CJ, Thomas MJ, Bourdeaux CP, Vasilakis C. COVID-19 scenario modelling for the mitigation of capacity-dependent deaths in intensive care. Health care management science. 2020 Jul 8: 23(3), 315-324. https://doi.org/10.1007/s10729-020-09511-7

[35] Alban A, Chick SE, Dongelmans DA, Vlaar AP, Sent D, Group S. ICU capacity management during the COVID-19 pandemic using a process simulation. Intensive Care Medicine. 2020 May 7:1. https://doi.org/10.1007/s00134-020-06066-7

[36] Wood RM. Triage modelling repository containing inputs, model code, and outputs. 2020. Available from: https://github.com/nhs-bnssg-analytics/triage-modelling

[37] Monks T, Currie CS, Onggo BS, Robinson S, Kunc M, Taylor SJ. Strengthening the reporting of empirical simulation studies: Introducing the STRESS guidelines. Journal of Simulation. 2019 Jan 2;13(1):55-67. https://doi.org/10.1080/17477778.2018.1442155

[38] Rashid M. Two decades (1993-2012) of adult intensive care unit design: A comparative study of the physical design features of the best practice examples. Critical care nursing quarterly. 2014 Jan 1;37(1):3-2. https://doi.org/10.1097/CNQ.0000000000000002

[39] Horsfield C, Platten JJ, Himsworth A, Berry A, Hill C. National critical care nursing and outreach workforce survey. Critical Care Networks National Nurse Leads. 2018. Available from:

http://www.cc3n.org.uk/uploads/9/8/4/2/98425184/national_critical_care_nursing_and_outreach_workforce_survey_report_2018_final.pdf.

[40] Kings Fund. Critical care services in the English NHS; 2020. Available from: https://www.kingsfund.org.uk/publications/critical-care-services-nhs

[41] Booton RD, MacGregor L, Vass L, Looker KJ, Hyams C, Bright PD, Harding I, Lazarus R, Hamilton F, Lawson D, Danon L, Pratt A, Wood RM, Brooks-Pollack E, Turner KM. Estimating the COVID-19 epidemic trajectory and hospital capacity requirements in South West England: a mathematical modelling framework. BMJ Open. 2021; 11:e041536. http://dx.doi.org/10.1136/bmjopen-2020-041536

[42] Office for National Statistics. Statistical Bulletin: National Life Tables, UK: 2016-2018. 2020. Available from: https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/lifeexpectancies/datasets/nationallifetablesunitedkingdomreferencetables

[43] Deasy J, Rocheteau E, Kohler K, Stubbs DJ, Barbiero P, Liò P, Ercole A. Forecasting ultra-early intensive care strain from COVID-19 in England. medRxiv. 2020 Jan 1. https://doi.org/10.1101/2020.03.19.20039057

[44] Phua J, Weng L, Ling L, Egi M, Lim CM, Divatia JV, Shrestha BR, Arabi YM, Ng J, Gomersall CD, Nishimura M. Intensive care management of coronavirus disease 2019 (COVID-19): challenges and recommendations. The Lancet Respiratory Medicine. 2020 Apr 6. https://doi.org/10.1016/S2213-2600(20)30161-2

[45] Childress JF, Beauchamp TL. Principles of biomedical ethics. New York: Oxford University Press; 2001.

[46] Kruser JM, Cox CE, Schwarze ML. Clinical momentum in the intensive care unit. A latent contributor to unwanted care. Annals of the American Thoracic Society. 2017 Mar;14(3):426-31. https://doi.org/10.1513/AnnalsATS.201611-931OI

[47] Armstrong RA, Kane AD, Cook TM. Outcomes from intensive care in patients with COVID-19: a systematic review and meta-analysis of observational studies. Anaesthesia. 2020 Oct;75(10):1340-9. https://doi.org/10.1111/anae.15201

[48] Horby P, Lim WS, Emberson J, Mafham M, Bell J, Linsell L, Staplin N, Brightling C, Ustianowski A, Elmahi E, Prudon B. Effect of dexamethasone in hospitalized patients with COVID-19: preliminary report. MedRxiv. 2020 Jan 1. https://doi.org/10.1101/2020.06.22.20137273

[49] NHS England. Second phase of NHS response to COVID-19; 2020. Available from: https://www.england.nhs.uk/coronavirus/publication/second-phase-of-nhs-response-to-covid-19-letter-from-simon-stevens-and-amanda-pritchard/