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Review Article

Forecasting the Binding Constraint: Respiratory Demand Prediction, Capacity Failure, and Its Economic Cost in Low- and Middle-Income Countries

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Abstract

Respiratory surges cause most of their losses as demand approaches a binding capacity constraint, yet recent published evaluations of the main forecast hubs score unweighted accuracy for counts. This narrative review argues that forecasts should be built and judged as warnings of constraint crossings, and that in low- and middle-income countries (LMICs) oxygen binds alongside beds and trained staff plausibly do, yet both are missing from almost all models. At the first peak of the 2024-2025 influenza season, only 6% of the FluSight ensemble's two-week 95% intervals across jurisdictions contained the observed admissions. Transformed-scale, allocation, and cost-loss scores each ranked respiratory forecasts differently from the score they were compared with, but no study we found addresses facility oxygen or uses LMIC data. Studies from five countries show in-hospital mortality rising with load, often below nominal capacity. In LMICs, 70% of people with acute oxygen needs lack adequate therapy. In a worked example at the 2026 UK ward design supply of about 6 L/min per bed, the probability that oxygen demand exceeds supply passes 0.05 ten days before the probability that occupancy exceeds beds does, so a bed-only forecast would miss the binding constraint. Most evidence comes from COVID-19 in high-income settings, so the LMIC conclusions are inferences that require prospective testing.

***Keywords**: Respiratory Forecasting; Hospital Capacity; Medical Oxygen; Forecast Evaluation; Cost-Loss; Early Warning; LMICs*

Introduction

Respiratory surges impose their costs at capacity thresholds

A hospital absorbs a rising respiratory caseload until beds, oxygen, staff, or equipment run short, and outcomes then deteriorate for every patient. Kadri., *et al*. [1] found that the adjusted odds of death or discharge to hospice among COVID-19 inpatients in 558 United States hospitals doubled in hospital-months above the 99th percentile of a surge index, and that 23.2% of deaths were potentially attributable to strain. French., *et al*. [2] estimated that national intensive care unit (ICU) occupancy of 75% would be followed two weeks later by about 12,000 excess deaths. Walker., *et al*. [3] projected that COVID-19 deaths under mitigation in a typical low-income country would rise from 2.1 per 1,000 with unlimited, high-quality care to 6.5 with capacity limits and poorer care.

The evaluation gap

The FluSight challenge of the Centers for Disease Control and Prevention (CDC) has scored onset, peak timing, and peak intensity [4], and its 2026-2027 challenge collects optional probabilities for rate-trend categories, peak week, and peak incidence [5], yet the published 2024-2025 evaluation scores only weekly admission counts with the weighted interval score (WIS) and interval coverage [6]. Threshold-

weighted proper scores [7] and weighted verification tools from meteorology [8] reweight evaluation toward chosen outcomes. Log-scale scoring reordered European COVID-19 forecasts relative to natural-scale scoring [9], allocation scores reordered US COVID-19 forecasts relative to WIS [10], and cost-loss value scores for FluSight peak-intensity forecasts from 2011/12 to 2017/18 bore no clear relationship to log-score rankings [11]. Allocation scores and occupancy-surge classifiers [12] come closest to capacity, using a hypothetical national resource limit and local US occupancy thresholds, but none of these studies addresses oxygen or uses LMIC data.

Scope, approach, and thesis

This narrative review traces the chain from demand forecast to capacity model to economic loss (Figure 1). We searched Crossref, Europe PMC, PubMed, Semantic Scholar, and the web for empirical sources from 1999 to 2026, added methodological references from any year, and prioritized LMIC evidence; Supplementary File S1 gives the search strings, inclusion criteria, and screening log. We did not appraise study quality formally. Our thesis is that respiratory demand forecasts should be built and evaluated as warnings of constraint crossings, and that in LMICs these constraints include oxygen and, plausibly, trained staff, which current models omit. Most forecasting evidence comes from COVID-19 in high-income countries, and we flag where conclusions may not transfer to seasonal influenza or respiratory syncytial virus (RSV).

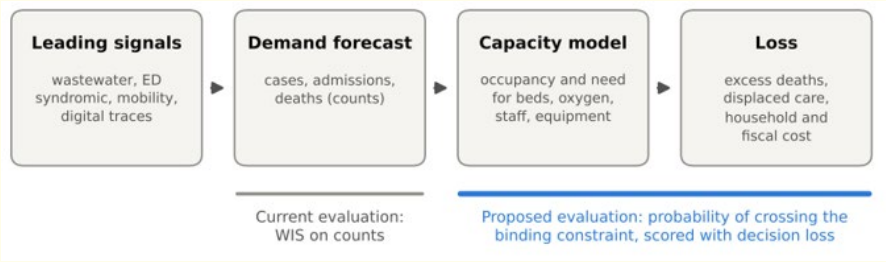


Figure 1: *The forecast-to-loss chain. Leading signals feed demand forecasts, capacity models convert demand into occupancy and resource need, and losses accrue as occupancy approaches and crosses the binding constraint.*

Forecasting respiratory demand: Methods and track record

Statistical and time-series models

Statistical models forecast routine demand well over short horizons. In São Paulo, in one of few LMIC evaluations, calendar-based models forecast daily emergency department visits with a mean absolute percentage error near 11% [13]. Meakin., *et al*. [14] found that a simple ensemble forecast COVID-19 admissions for English hospital trusts with 29% less probabilistic error than a no-change baseline at 7 days, with the largest gains while admissions were falling. Such models extrapolate the current regime and lose skill at the turning points that matter for capacity.

Mechanistic and scenario models

Compartmental models support scenario analysis, but their reliability decays with horizon. Howerton., *et al*. [15] found that unanticipated variants appeared a median of 16 weeks into US Scenario Modeling Hub projection periods, and that for periods of increasing incidence the hub ensemble had 45% precision and 24% recall. No scoring rule corrects that failure, because it arises from a change in the pathogen rather than in calibration.

Ensembles and forecast hubs

Multi-model ensembles are the most consistently calibrated forecasts. Reich., *et al*. [4] found that 15 of 22 influenza models beat a historical baseline in at least six of seven seasons one week ahead, but only 7 did so four weeks ahead. The US COVID-19 Forecast Hub ensemble had a relative WIS of 0.61 and beat the baseline in every location, and a post hoc analysis of selected waves found that models underpredicted deaths while trends were rising [16]. The FluSight ensemble's 95% interval coverage for influenza admissions fell in 2022-2023 to 29% in its worst week at the one-week horizon and 15% at four weeks [17]. At the season's first peak on 4 January 2025, only 6% of its two-week 95% intervals across jurisdictions contained the observed values, and because of this performance CDC first published the season's forecasts on 5 March 2025 [6].

Machine learning and digital traces

Machine-learning models have mostly been built on narrow, single-country data. In the fourth update of their living review, Wynants., *et al*. [18] rated 545 of 606 (90%) COVID-19 prognostic models at high risk of bias and found that 92% used data from a single country.

From demand to occupancy: Capacity models

Occupancy thresholds and queueing

Random variation in arrivals and length of stay means that a hospital running near capacity on average will often exceed it. Bagust., *et al*. [19] found in simulation that bed shortages became discernible above about 85% average occupancy. Kuntz., *et al*. [20] analyzed 82,280 patients in 83 German hospitals and estimated a mortality tipping point at 92.5% occupancy. Runge., *et al*. [21] found that triggering mitigation at 80% ICU occupancy in Chicago did not prevent overflow under any mitigation strength, and that thresholds of 40% to 60% were needed to hold overflow risk to 25%. The actionable threshold therefore sits below nominal capacity.

Length-of-stay and bed-occupancy simulation

Occupancy models convert admissions into census, and their error depends on length-of-stay assumptions. Baas., *et al*. [22] modeled ward and ICU occupancy as a queueing network and achieved 90% to 99% interval coverage for ICU census one to five days ahead in Dutch hospitals. Rees., *et al*. [23] found a pooled median hospital stay of 14 days in China and 5 days elsewhere, so a borrowed parameter can shift projected occupancy several-fold.

Oxygen, staff, and equipment as missing constraints

Almost every model reviewed here represents capacity as beds or ICU beds and adds ventilators at most [3,24]. Oxygen demand models exist but are rarely linked to admission forecasts. Bradley., *et al*. [25] found that simulated pediatric pneumonia oxygen demand exceeded estimates based on annual averages 43.8% of the time in the high season. In critically ill COVID-19 patients, Huth., *et al*. [26] measured median flows of 40 L/min for high-flow nasal cannula and 3.2 L/min for mechanical ventilation, so oxygen demand depends on the mix of delivery modes, which a bed forecast does not capture.

The economics of running out

Strain-mortality relationships

The health cost of strain is the best-measured link (Figure 2). Kadri., *et al*. [1] found adjusted odds rising from 1.11 at the 50th to 75th surge percentile to 2.00 above the 99th. Rossman., *et al*. [27] found that 14-day mortality among Israeli inpatients exceeded predictions by 22.1% and 27.2% in two high-load periods, with excess deaths appearing above about 500 severely ill patients nationally, well below the official capacity of 800. In South Africa, in-hospital case fatality rose from 17.7% in weeks of low national admissions to 26.9% in weeks of very high admissions (adjusted odds ratio 1.24) [28]. Wilde., *et al*. [29] found that admission to English ICUs above 85% occupancy raised the odds of death by 23%, with a linear rather than kinked relationship. These are observational estimates subject to residual confounding [1], and South Africa's second wave carried 31% higher mortality after adjustment for load [28].

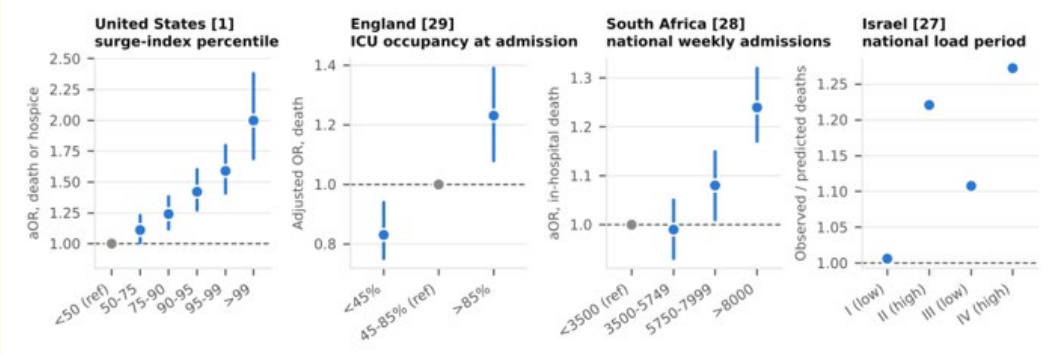


Figure 2: *Mortality by hospital load, one panel per setting and metric: United States surge-index strata [1], English ICU occupancy bands [29], South African weekly admissions [28], and Israeli observed-to-predicted mortality [27].*

Staffing, displaced care, and household costs

Needleman., *et al*. [30] found that each shift with registered-nurse staffing eight or more hours below target raised the hazard of death by 2%, so a prolonged surge erodes outcomes even when beds remain open. Boniol., *et al*. [31] projected that the African region would hold 52% of the global health worker shortage in 2030. The COVIDSurg Collaborative [32] projected cancer surgery cancellation of 70.2% in low-income and 30.3% in high-income countries during 12 weeks of peak disruption. In Chhattisgarh, India, catastrophic expenditure followed 3.2% of public and 58.9% of private COVID-19 hospitalizations [33].

Monetizing strain and the cost-loss rule

Valuing each death at the US$7 million used by Cutler and Summers [34], the 5,868 deaths that Kadri., *et al*. attributed to surge strain [1] represent about US$41 billion in six months; the figure is an upper-range illustration because Kadri., *et al*. called these deaths potentially attributable. For LMICs, Robinson., *et al*. [35] recommend extrapolating from a US value per statistical life of US$9.4 million with an income elasticity of 1.5 and a floor of 20 times gross national income (GNI) per capita, which gives about US$318,000 for India at its 2015 GNI per capita of US$6,060 at purchasing power parity. The cost-loss rule is to act at cost C when the forecast probability of a loss L exceeds C/L [36]. With C and deaths averted fixed, the income-scaled value raises C/L about 30-fold relative to a uniform US$9.4 million, so a facility that would act at a probability of 0.001 would wait until 0.03. Income scaling therefore delays action where capacity is scarcest, and analyses should report decisions under both values or use disability-adjusted life-years (DALYs). Prevention can be cheap on either scale: improved oxygen systems in Papua New Guinea cut pediatric pneumonia mortality by 35% at US$1,673 per life saved and US$50 per DALY averted [37], and closing the acute oxygen gap in LMICs would cost an estimated US$6.8 billion a year [38].

Early-warning signals

Wastewater and syndromic surveillance

Leading indicators extend warning time, but studies measure leads against different targets (Figure 3). SARS-CoV-2 RNA in New Haven sewage sludge led local hospital admissions by one to four days [39], and wastewater in Athens led hospital admissions by eight days and ICU admissions by nine [40]. Olesen., *et al*. [41] tabulated lead times of 0 to 14 days against reported cases, including 14 days in Gandhinagar, India. Emergency department respiratory attendances in England rose about one week before RSV laboratory confirmations [42].

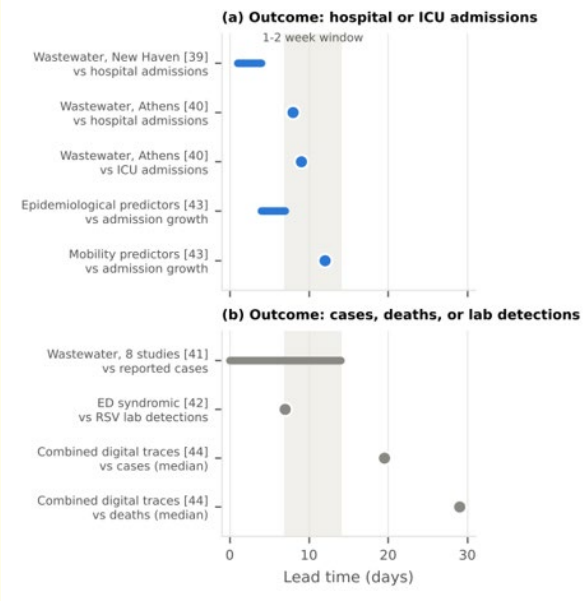


Figure 3: *Reported lead times of early-warning signals, in separate panels by the outcome each study measured: (a) hospital or ICU admissions [39,40,43]; (b) cases, deaths, or laboratory detections [41,42,44].*

Digital traces and critical slowing down

Kogan., *et al*. [44] combined five digital data streams into an indicator that preceded state-level case increases, not hospital admissions, by a median of 19.5 days. Adding epidemiological and mobility predictors that led admission growth by 4 to 12 days halved the 14-day error of French admission forecasts [43]. Statistical early-warning indicators are less reliable: only variance consistently beat a random classifier for COVID-19 second waves, and indicators overall performed worse than random in a set that pooled Denmark, Israel, and Nepal, where the theory's assumptions failed [45].

LMICs: Where the methods break

Data scarcity and under-ascertainment

Models fitted to reported counts inherit their biases, which are large in many LMICs (Figure 4). The World Health Organization estimated 14.83 million excess deaths in 2020 and 2021, 2.74 times the reported COVID-19 toll [46]. Jha., *et al*. [47] estimated 3.2 million COVID-19 deaths in India from June 2020 to July 2021 and found cumulative deaths by September 2021 six to seven times the official count. Murhekar., *et al*. [48] found 24.1% seroprevalence in India by January 2021, which implied 27.1 infections per reported case.

Binding constraints beyond beds

No study has measured directly which resource runs out first. The evidence shows beds and oxygen binding, with staff shortages a plausible third constraint. The Commission on medical oxygen security estimated that only 30% of the 299 million people in LMICs with acute oxygen needs receive adequate therapy and that missing supply data make stockouts "common and unpredictable" [38]. In Kenya, only 37,216 of 64,181 hospital beds (58%) were in facilities with oxygen [50]. The African COVID-19 Critical Care Outcomes Study found a median of two intensivists per hospital, admission of only 55.3% of patients referred for critical care, and doubled odds of death after resource-driven admission delay [51]. At a South Indian referral hospital, the share of second-wave inpatients treated with oxygen rose by half while the share needing ICU admission did not change [52].

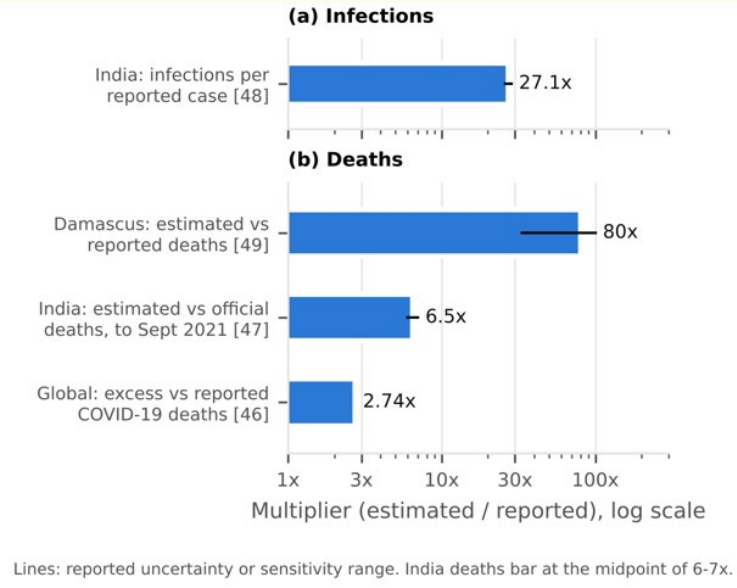


Figure 4: *Under-ascertainment in LMIC settings, log scale, with infections and deaths in separate panels: (a) Infections per reported case in India [48]; (b) Estimated to reported deaths globally [46], in India [47], and in Damascus [49].*

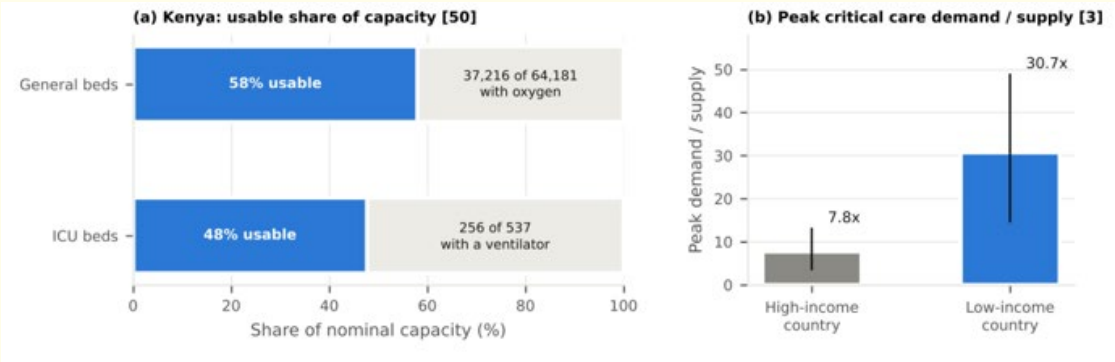


Figure 5: *(a) Kenya: share of nominal bed and ICU capacity usable once oxygen and ventilators are counted [50]. (b) Peak critical care demand relative to supply under mitigation, typical low- versus high-income country [3].*

Case evidence: Manaus, India, Brazil, and South Africa

The 2021 capacity failures combined regime change with missing constraints. In Manaus, COVID-19 admissions rose from 552 in 1-19 December 2020 to 3,431 in 1-19 January 2021 despite estimated 76% seroprevalence; Sabino., *et al*. weighed overestimated attack rates, waning immunity, and new lineages including P.1 [53]. Delhi was more than 50% seropositive by 2021, yet was overwhelmed in April 2021 as Delta replaced Alpha, with an estimated 1.5-fold greater transmissibility and 20% lower sensitivity to prior immunity [54]. The Lancet reported that modeling had suggested herd immunity before India's second wave and that Uttar Pradesh and Maharashtra then ran out of oxygen and hospital space [55]. Compared with Brazil's South, the Northeast had fewer ICU beds per 100,000 (18 versus 23) and higher in-hospital mortality under age 60 (31% versus 15%) [56]. South Africa's second wave grew at 43% per week against 20% in the first [28].

Transferability

Every demand-forecast evaluation in Section II except the São Paulo study [13] comes from a high-income country, so the claim that LMIC forecasts will fail at surges is an inference from capacity and data evidence rather than a measured result. High-income assumptions also travel badly: Kenyan surge estimates used United States severity risks [50].

Toward constraint-aware forecasting

Score forecasts on threshold exceedance and decision loss

For two-week-ahead forecasts of US COVID-19 admissions on 3 January 2022, the model with the best allocation score had a mean WIS of 133, while the model with the second-best WIS ranked third-worst on allocation [10]. Murray-Watson., *et al*. [12] framed forecasting as classification of local occupancy surges and outperformed CDC Community Levels. Lerch., *et al*. [57] showed that evaluating forecasts only on extreme outcomes can discredit skillful forecasts when the signal-to-noise ratio is low, which they called the forecaster's dilemma, and discussed proper weighted scores as the remedy [7,8]. Bracher., *et al*. [58] defend WIS's sensitivity to distance as useful for bed planning, and a threshold-weighted score keeps that property while weighting outcomes near capacity. Hubs could publish the probability that occupancy or oxygen demand will exceed local thresholds and score it with threshold-weighted and cost-loss scores alongside WIS.

A worked example: Forecasting an oxygen constraint

Figure 6 chains the parameters in table 1 into an oxygen forecast for a hypothetical 200-bed facility that admits only respiratory patients. Admissions grow at the South African second-wave average of 43% a week [28], without saturation for 21 days. At a South Indian referral hospital, 63.6% of second-wave inpatients were treated with supplemental oxygen and 30.9% received non-invasive ventilation (NIV), which that hospital started for respiratory failure [52]. We assume that NIV patients are a subset of those treated with oxygen and give them the planning flow for critical illness. At the World Health Organization planning flows of 10 L/min for severe and 30 L/min for critical illness [26], mean demand is (0.636 - 0.309) × 10 + 0.309 × 30 = 12.5 L/min per occupied bed. Giving NIV patients the measured high-flow median of 40 L/min [26] for a median of 3 days and then 10 L/min, or for the whole stay, gives 11.6 or 15.6 L/min. Base supply is the in-patient ward design flow of the 2026 UK standard, 15 + 6(n - 1) L/min, or about 6 L/min per bed [59]. At that supply, P(oxygen demand > supply) passes 0.05 on day 10 and 0.30 on day 13, while P(occupancy > 200 beds) reaches 0.05 only on day 20. A bed-only forecast would miss the binding constraint by 10 days, or by 15 if NIV patients receive high flow throughout. The lead shrinks as supply rises and vanishes above about 12, 11, or 15 L/min per bed under the three flow scenarios (Figure 6d). At 20% weekly growth [28], occupancy never reaches 0.05 within 21 days, while oxygen does on day 15. Because the parameters come from South Africa, India, a multi-country review, and an international ICU registry, the example shows mechanics rather than any facility's risk.

Parameter	Value	Source
Facility	200 beds; 6.0 L/min oxygen per bed (sweep 2-16)	Assumed; [59]
Admissions	8 a day at day 0 (census 44 after a 30-day pre-history); 43% weekly growth (20% sensitivity); log-growth SD 0.12; negative binomial size 20	[28]; assumed
Oxygen; NIV	63.6%; 30.9% of inpatients	[52]
Length of stay	Weibull fit to median 5 days (IQR 3-9)	[23]
Flows	Oxygen alone 10 L/min; NIV 30 L/min, or 40 L/min for a median 3 days (IQR 2-6) or the whole stay	[26]

Table 1: *Worked-example parameters.*

Staffing could be forecast from the same census at the 1:2 nurse-to-patient ratio of African critical care units [51], but we found no LMIC data on facility nurse supply, so we leave it unmodeled.

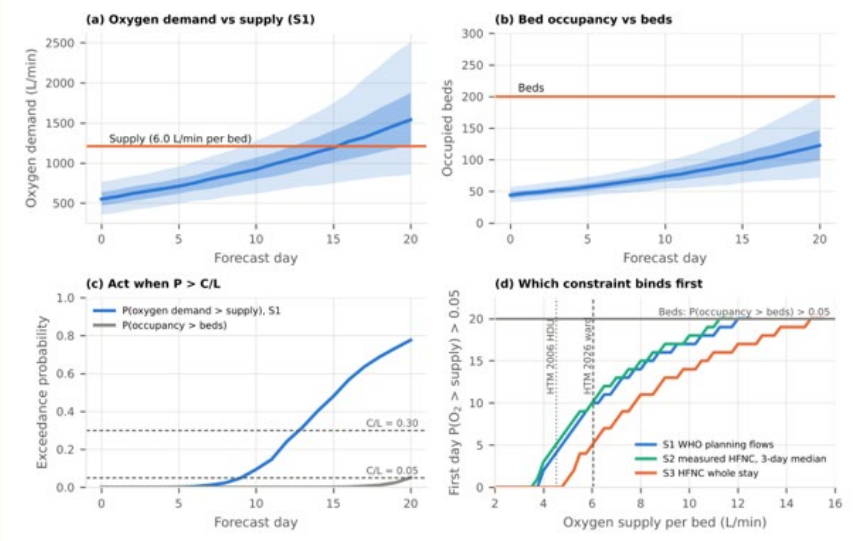


Figure 6: *Worked example; parameters in table 1. (a) Oxygen demand against supply, base flows. (b) Occupancy against beds. (c) Exceedance probabilities with cost-loss thresholds [36]. (d) First day on which P(oxygen demand > supply) exceeds 0.05, by supply per bed and flow scenario; vertical lines mark UK design rates.*

Pair cheap leading signals with simple capacity models in low-data settings

Where testing is sparse, wastewater [41] and all-cause mortality [49] are independent of testing, and emergency department syndromic data are routinely collected [42]. Transparent occupancy models with locally estimated length of stay [23] are more defensible than complex transmission models fitted to biased counts [18,60]. Prospective evaluation of these signals and of oxygen forecasts in LMIC facilities is the most urgent empirical gap.

Conclusion

Losses from respiratory surges rise with hospital load, often below nominal capacity, and in LMICs oxygen binds alongside beds, staff plausibly do, and reported data understate burden. Scoring theory and decision analysis supply tools to evaluate forecasts against these constraints, but no study we found applies them to facility oxygen or to LMIC data. Threshold-weighted and cost-loss evaluation, oxygen forecasts derived from census forecasts, staffing models built on local nurse supply data, decisions reported under uniform and income-scaled values of life, and prospective tests of low-cost leading signals in LMICs are the steps most likely to connect forecasts to the losses they are meant to prevent.

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