Informatics in Medicine Unlocked 24 (2021) 100618

Contents lists available at ScienceDirect

Informatics in Medicine Unlocked

journal homepage: www.elsevier.com/locate/imu

Decision support tool for hospital resource allocation during the COVID-19 pandemic

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ARTICLE INFO

Keywords:
Real-time resource planning
COVID-19
SARS-CoV-2
In-house patient modeling
Resource allocation
Staffing
Web application
Emergency planning
Contingency planning
Scenario simulation
Ensemble simulation
Erlang distribution

ABSTRACT

The SARS-CoV-2 (COVID-19) pandemic has placed unprecedented demands on entire health systems and driven them to their capacity, so that health care professionals have been confronted with the difficult problem of ensuring appropriate staffing and resources to a high number of critically ill patients. In light of such high-demand circumstances, we describe an open web-accessible simulation-based decision support tool for a better use of finite hospital resources. The aim is to explore risk and reward under differing assumptions with a model that diverges from most existing models which focus on epidemic curves and related demand of ward and intensive care beds in general. While maintaining intuitive use, our tool allows randomized "what-if" scenarios which are key for real-time experimentation and analysis of current decisions' down-stream effects on required but finite resources over self-selected time horizons. While the implementation is for COVID-19, the approach generalizes to other diseases and high-demand circumstances.

1. Introduction

The novel COVID-19 pandemic has created an unpreceded global strain on healthcare systems. This crisis has exacerbated already existing tensions within hospital systems which need to balance costs, quality of care, capacity and efficiency [2,7,9,25,28,29,32,39,52,56,58,61]. Overcrowded intensive care units (ICUs) present a complex challenge to administrators who are plagued by having to judge who will receive treatment and who will not, since admitting a patient today means potentially not being able to admit a needier patient tomorrow [50,53,63,66]. By way of a simple example, a 100-bed hospital currently 85% full will quickly exceed capacity if they admit more than a single patient per day given a roughly 13-day average stay for COVID-19 patients. Similarly, staffing [26,38], medications and equipment including ventilators, extracorporeal membrane oxygen (ECMO) and dialysis machines [8,54] are all finite resources.

The admission and discharge dilemma deepens as the decision's down-stream effects on the short-term demand of these limited in-house resources are difficult to predict due to various interdependent time- and space-varying factors. For instance, patient heterogeneity represents a challenge since demand depends on each patient's length of stay (LOS), which requires knowledge of individual patient pathways [64], and LOS itself affects possible configurations of staffing. For example, patient characteristics such as age and comorbidities impact disease severity, and general ward-based care requires different staff and equipment support than does intensive care. Next, short-term demand of in-house resources also depends on required combinations of health care providers and ancillary staff, as well as physical resources and medications needed at a particular time [55,57,60]. Other factors affecting short-term demand's unpredictability are the increase in efficacy of treatments and knowledge, and quantitative uncertainty of new COVID-19 patients. The latter is attributed to altering case rates, for instance as a result of local community outbreaks, emerging variants [48], related change in vaccine efficacy [20], and success in the vaccine rollout [36]. A further factor for uncertain short-term demand is that decisions about who will be admitted and discharged may alter over time as health care systems approach capacity [63,66]. Indeed, and as with COVID-19, understanding of the disease and of the efficacy of various treatment options varies with the course and duration of the outbreak.

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https://doi.org/10.1016/j.imu.2021.100618
Received 23 April 2021; Accepted 22 May 2021
Available online 1 June 2021

The aforementioned factors render recent research on models that solely predict the number of COVID-19 patients as requiring extension to act as a support tool for decision makers in resource management. Among those models, there are predictions of rates of community-based diseases [1,6,30,31,62], rates of hospitalization [22,41,65] and ICU demand [19,33,44,59], which are often based on estimated epidemic curves [21,35,37]. Another hurdle in using such general models for in-house resource prediction is the fact that operations are facility specific, e.g., academic health systems such as the University of California, San Diego (UCSD) and non-academic facilities typically compose teams very differently and adapt them to current demand.

Simply, there is a lack of systematic integration of current decision's impact on future capacity, associated staff and ancillary support requirements, and hence absence of methodical support for health care professionals in their decision making. To address this gap of resource provision and allocation, and initiate a broad collaboration, as advocated for in e.g. Ref. [42], UCSD Emergency and Pulmonary Medicine chiefs specified their challenges and wishes to engineers at UCSD Jacobs School of Engineering, to model down-stream effects via randomized "what-if" scenarios with local inputs over self-selected time horizons, using an open easy-to-use web application. In this way, our developed tool explores the level of uncertainty by randomized simulations and hence helps to quantify the likelihood of hitting constraints or, alternatively, underusing capacity. A related feature is the ability to adjust descriptors of patient and process evolution, primarily modeled by the LOS probability. Overall, our tool allows healthcare workers to explore the effects of their decisions under different circumstances in order to provide valuable insights and crucial data for decision-making and contingency planning early on. In addition, as user inputs may be aligned to predicted infection rates provided by general models such as those introduced above, our tool leverages recent research under consideration of facility-specific factors and constraints. While we focus here on COVID-19 and its attendant resource implications pertinent to our Southern California, the approach is amenable to other high-stress extended emergencies. A number of limitations and refinements, including tuning with data, is presented toward the end. We emphasize that the focus of this work is the presentation of the tool itself and the benefits of using "what-if" scenarios with sensible and computable densities. A validation of predicted consumed resources against data will be part of a future investigation.

A remarkable recent paper on optimal hospital care scheduling models each individual patient as a scalable dynamic program [18]. The model encodes health and treatment conditions and considers resource constraints. However, the model requires known transition probabilities between patient states; these probabilities are unavailable for many regions. Further, the computationally costly optimal solution of the dynamic program does not allow the user to examine different scenarios in real time.

2. Methods

To support local health system administrators and division chiefs in the problematic decision of admitting and discharging COVID-19 patients, and in the corresponding contingency planning, we describe a tool that uses local inputs to simulate demand for finite and interdependent resources such as staff, medication and medical equipment under different circumstances over a self-selected time horizon in a stochastic fashion. Stochasticity is an essential ingredient and refers to the randomness of individual patient response, which is aggregated and smoothed over the many patients to permit an exploration of all possible, including rare, outcomes. In the remaining part of this section, we present the tool in more detail.

Given our requirement of an easy-to-use graphical interface, the ability to conduct randomized "what-if" experiments with different configurations of staffing, infrastructure support and intervention strategies (for example, a change in protocol for who is to be ventilated) and independence of operating systems, a web application (Fig. 1) has been developed that provides "what-if" simulations of finite resource requirements based on anticipated new arrivals and user input.

2.1. User inputs

The resource requirements are computed given user-specified input parameters: prediction time, number of initial patients per day and arriving COVID-19 patients per day, number of consultations per patient per day, resource consumption per patient per day, and average number of days in the ICU, on ECMO, ventilator and dialysis. The web application's simple user interface, manageable number of input parameters, real-time computation, graphical display of output variables, and intuitive visualizations render it a useful tool for most health systems. The interface is depicted in the figure below. The particular selection of input parameters is based on the likelihood of shortages of resources that have occurred during the pandemic at UCSD health system, primarily caused by COVID-19 patients.

On the left side, the input variables are selected, displayed and set. The output of the simulation is pictured on the right side of the figure. The inputs specify the parameters of the simulation and the outputs the associated random resource consumption. The views are user selected.

2.2. Outputs

The user specifications are used as inputs to the simulation to predict the required number of resources per shift, assuming two shifts per day. Currently, we consider propofol, dexmedetomidine, fentanyl, morphine, morphine [oral], oxycodone, cisatracurium and vecuronium as critical medication. Additionally, the model computes the required number of computer-aided tomography (CT) scans, magnetic resonance imaging (MRI) scans, personal protective equipment (PPE), ventilators and ECMO circuits per day. A further simulation output is the required number of consultations per day. In this way, the simulation is independent of particular team constellations. As with the inputs, the choice of outputs is motivated by the corresponding likelihood of hitting constraints at UCSD health system, primarily related to COVID-19 patients.

2.3. The simulation

Towards a computation of required resources, our tool generally differentiates between patients being in the ICU but not undergoing invasive mechanical ventilation ("ICU Bed"), being in the ICU on a ventilator ("Ventilated") and being in the ICU on ECMO ("ECMO"). For patients on "ECMO" the user specifies the average number of days in the ICU, on ECMO and on dialysis, respectively. The average is a parameter of the Erlang distribution. This distribution is familiar from telecommunications and the modeling of arrivals of multiple calls [13]; hence the connection between blocked calls and resources. It is well suited to describe the number of days in the ICU/on ECMO/dialysis as its support is strictly positive, i.e., the probability of negative numbers of days is zero, and it has a tunable long tail, i.e., it accommodates the possibility of some patients being in the ICU/on ECMO/dialysis for a long time while most patients remain substantially a shorter time period in the respective stage. Similarly, for patients in the category "Ventilated" the user selects the average number of days in the ICU, on a ventilator and on dialysis, respectively, also based on distinctly parametrized Erlang distributions. For the category "ICU Bed" the user defines the average days in the ICU and on dialysis, related to the Erlang distribution, too. To keep the inputs manageable, we assume that patients on ECMO additionally require a ventilator for an average of three days after being on ECMO, that patients in the "Ventilated" category do not require ECMO and that patients in the category "ICU Beds" neither need ECMO nor a ventilator.

Given the user-specified averages and number of new arrivals per day per category, for each arriving patient the tool randomly assigns a

Fig. 1. User interface of web application numbat.ucsd.edu/∼sven/covid with user-selected input variables on the left-hand side and model outputs on the right-hand side. Changes in input variables re-initialize a new simulation with instantaneous corresponding model outputs.

number of days in the ICU, on ECMO, dialysis and ventilator, drawing from the corresponding Erlang distribution using the formula [14],

$$E(k,\mu) = -\frac{1}{\mu}\log \prod\nolimits_{i=1}^{k} U_i,$$

with random variable U_i uniformly distributed between zero and one, and μ (k) commonly known as the rate (shape) parameter. The simple form is a result of the fact that the Erlang distribution can be expressed as a sum of k independent exponentially distributed random variables. For the initial patients, the same procedure applies, but is followed by a random selection uniformly between zero and the initially assigned number of days. The randomly assigned time durations for each patient and corresponding use of resources defined by the other user inputs, when aggregated over the number of patients, determine the simulation outputs. A more detailed description of our algorithm is provided in the flow chart of in Fig. 2. Therefore, the randomly generated model outputs change even in the case of identical input parameters and support the user in understanding the variance of the underlying process. Since the simulations are computed in real-time, they can, of course, be run multiple times to assess this outcome variability.

3. Results

The web application is an open web-accessible tool that provides predictions of resource consumption through "what-if' scenarios based on local user specifications and circumvents the task of accurate local predictions of new COVID-19 patients and disease progression. The use of Erlang distributions respects the stochastic nature of the underlying disease progression. The user interface of our tool, which is displayed in Fig. 1, is optimized for mobile and as well as desktop devices via a responsive design and can be accessed from any operating system; the computations are performed on the web host computer in real time. The visualizations of the distributions related to the user-selected averages provide an intuitive understanding of the input variables (Fig. 4).

The option of exporting the simulation results to a CSV file enables connectivity to other software suites. Our focus is on "what-if" scenarios and the presentation of the tool itself rather than its validation against data of COVID-19 patients. Thus, we will include a quantitative analysis

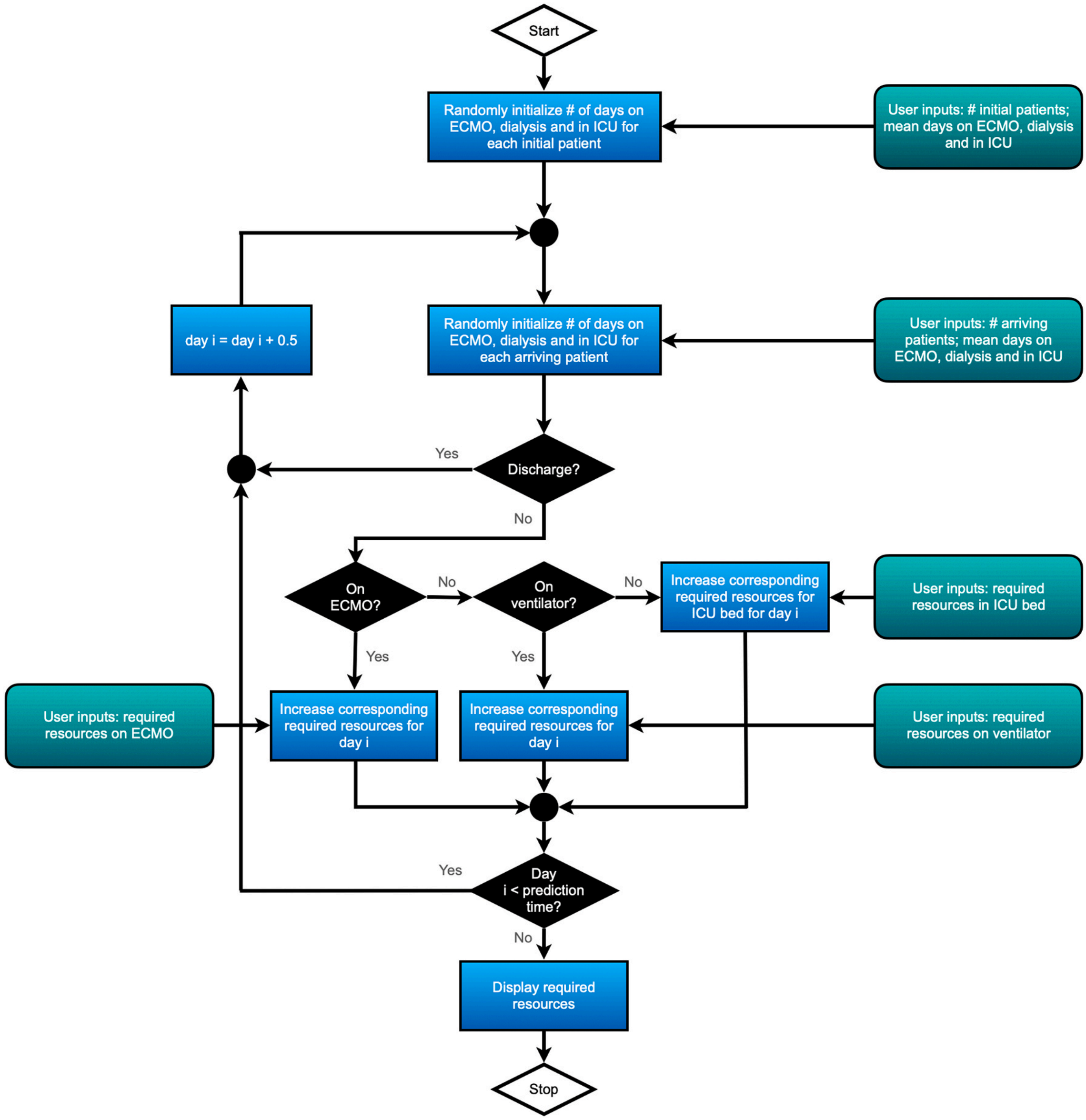

Fig. 2. Simplified flow chart of simulation with green-gradient boxes related to user inputs, blue-gradient boxes as computations and black diamonds as if-conditions. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

against real-world data and commercial tools in this area in a future work.

4. Discussion

The main feature of our tool is the accommodation of stochasticity related to the patient development while using user-provided deterministic information on arriving patients and corresponding resource consumption, leading to computationally fast "what-if" scenarios. This modeling approach supports the decision maker in several ways.

4.1. Assistance for decision makers

As commented on in the introduction, even with an accurate model of the outbreak progression of the regional population including disease severity and required PPE such as CHIME [46], a deterministic and aggregated nature allows at best an assessment of the short-term average number of arriving patients and related staff and resource requirements. However, it is difficult to model each individual, their corresponding medical history and status, and myriad important facility-specific external factors such as local community outbreaks, traffic patterns, transportation schedules, local policies etc. common in health care settings [3,23,24]; R [27,43]. Consequently, without any support, it is an intractable challenge for decision makers to predict the highly varying staff and resource requirements and provide any statistical smoothing over many patients. Additionally, data-based models face their own challenges as availability, reliability and viability of different data types limit their accuracy, such as representativeness, bias, uncertainty, time delay and local differences [49,55].

Therefore, our tool does not attempt to predict the number of arriving patients and related required staff and resources but, instead, assists the decision maker by solving the in-house problem of what happens *if* a certain number of COVID-19 patients arrives in need of a certain treatment, based on which staff and resource requirements are computed. This "what-if" scenario takes into account stochasticity of disease progression by drawing a sample from user-adjusted set of distributions. In this way, through a repetitive execution of different scenarios that in the user's opinion may occur, potentially informed by an outbreak progression model such as CHIME, our tool conveys the stochastic nature of the underlying process and helps the user preparing for

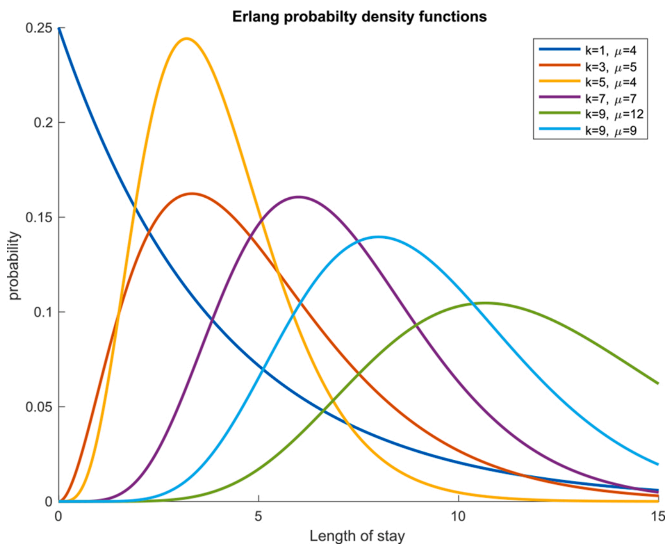

Fig. 3. Set of Erlang distributions for different shape parameters k and scale parameters mu with positive support, mean of k/μ and variance of k/μ^2. Long tails are related to a large variance and can be accommodated by appropriately choosing parameters k and μ.

future demand and contingency planning.

The stochastic nature is captured by allowing patient variability through different categories and their associated LOSs, modeled through Erlang distributions. These distributions are well-suited for our purpose. Firstly, they possess two parameters which directly determine the mean value and the shape, notably the significant tail probability of very long stays, as shown in Fig. 3, which places the density in the super-gaussian category [11]. Secondly, the closed-form description stated earlier allows to efficiently generate random samples using a standard random number which is crucial for real-time ensemble approaches such as ours.

A further problem the tool tackles deals with the utility function the decision maker is required to maximize. It permits the user to specify and plot all of the variables of interest to inform the practitioner's judgment. More precisely, by admitting new COVID-19 patients the user faces a multivariate, time-varying, multiobjective optimization problem; balancing costs, quality of care, capacity and efficiency [2,7,9,25,28,29,32,39,52,56,58,61]. A quantitative formulation of the overall criterion and constraints is generally difficult as it depends on each user's preferences and institutional regulations, as well as unknown disease progressions and new arrivals. However, our web application supports the user in determining their individual utility function through "what-if" scenarios by computing the criteria of required staff and resources. This can be leveraged by the user, assuming their expertise in assessing the requirements' correlations to other criteria of their individual utility function and hence weighting them amongst each other.

4.2. *Clinical needs and consequences*

Hospital and ICU strain is associated with worse patient outcomes and this has been more pronounced by COVID-19 [16,34]. During this pandemic, healthcare administrators have been forced to make decisions about resource allocation and staffing when needs, or anticipated needs, have outstripped resources. Inappropriate distribution and shortages of equipment have resulted in patient harm, provider burnout and economic damage to hospital systems. A clear benefit of our tool is to help in surge planning and assist administrators in preparing for "what if" scenarios regarding future resource needs, and staff acquisition and allocation. It enables hospital systems to prepare for future needs more accurately and plan how to use finite resources more appropriately when faced with patient care surges as has occurred during this pandemic. This would prevent undesirable scenarios, such as rationing of care in the ICU or unproven methods of administering care, such as splitting ventilators between patients.

Even if such resources are present, an adequate number of healthcare workers, such as respiratory therapists, nurses and physicians are required to provide high-quality care. Prior data have demonstrated a clear relationship between appropriate number of healthcare workers and improved outcomes and quality of care [4,45,47]. Additionally, proper staffing levels may decrease provider burnout, a major public health concern caused by the current pandemic [40,51]. Our tool can help determine the number of healthcare workers required to appropriately staff a hospital during a surge or predicted surge and inform administrators of the need to reach out to federal or state agencies, if required for emergency assistance. In this way, patient outcomes may be improved by determining the optimal number of healthcare providers required to appropriately staff ventilators and ECMO circuits required to provide quality care.

Similarly, hospitals can plan accordingly to adjust their services if such a tool can predict down-stream effects of anticipated demand via "what-if" simulations in real time. For example, in anticipation of a COVID-19 surge in the spring, many health systems cancelled elective procedures and surgeries in order to free inpatient care space. Because these services provide a large positive margin to the hospital bottom line, when the COVID-19 surge did not materialize in Spring 2020 in many regions, hospitals suffered significant financial losses, potentially impairing their ability to continue operations [5,12,15]. Use of this tool may help guide administrators in real time to determine an appropriate time and number of elective procedures that can be safely performed without causing harm to COVID-19 patients.

Additionally, this tool can help administrators more appropriately respond to and redistribute resources if an anticipated surge does not occur. For example, during the initial surge in New York City, many

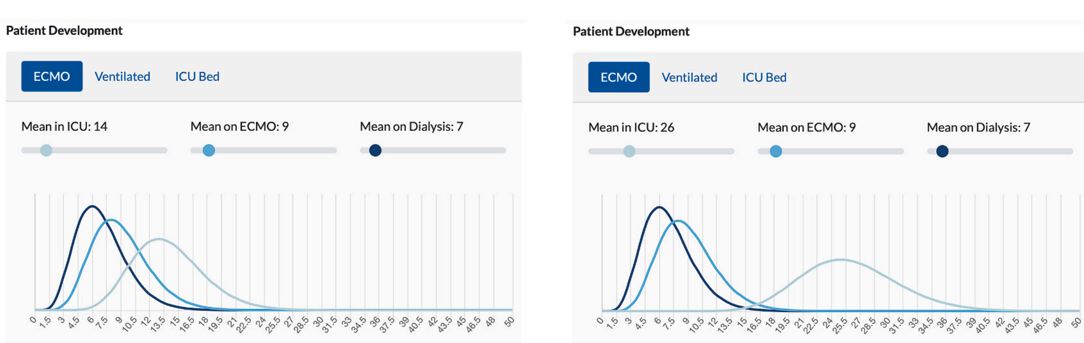

Fig. 4. The average number of days in the ICU, on ECMO and dialysis is visualized by their respective probability density functions. Changes in average days such as that from 14 to 24 in ICU (picture on the left/right-hand side) lead to a direct change in the related probability density function.

hospital systems outside of New York extensively stockpiled resources and changed staffing models for a surge that was either delayed or never came [17].

4.3. Limitations

Although we are confident that our tool provides meaningful predictions about resource availability, we acknowledge several limitations. First, we limited the number of inputs to the tool and recognize that other hospital systems may have other inputs that are critical to resource allocation. Next, we did not prospectively validate our findings, however, as mentioned above, our objective is to provide healthcare workers with "what if" scenarios. Finally, we realize that newer therapies for COVID19 may impact parameters such as need and duration for life-support therapies (e.g. ECMO, dialysis). However, we are able to adjust these if significant changes arise.

4.4. Refinements

The simulation app can be improved by more exact modeling capturing more detail of the observed resource usage. However, there is a utility-verisimilitude tradeoff which needs to be preserved to address the time availability of the users. The following adaptations are envisaged.

i. The densities used could be replaced by those fitted to real-world data capturing experience. These would replace the two-parameter Erlang densities and could be removed from the list of items required to be user input. This would not add significant computational burden and improve both utility and credibility. Particularly, this might apply to duration of dialysis and to known delays which are better modeled by specific densities different from Erlang.
ii. At present, the user specifies the patient arrival rates. This could be amended to include an option to access online community databases.
iii. Both features above could be included to provide a warm start for the user before exploring further scenarios.
iv. Variants of the app tailored to emergencies different from COVID-19 could be developed. Earthquakes and other multiple-casualty incidents are pertinent examples. The resource demands would change to reflect the nature of the events.
v. Further, as explained above, discretionary factors at the hospital level might be incorporated as policies in the simulation. These might include changes to treatment of elective surgeries or to the adoption of different discharge routes to long-term acute care facilities.

Each of these modifications would be adopted to adjust the input and evolution of the scenarios, while preserving the utility of the app.

5. Conclusion

This publication presents an accessible, flexible tool that meets the need of local health care professionals for a more systematic examination of down-stream effects of current decisions under varying and interdependent conditions, to detect a shortage of finite resources such as staff, medication and medical equipment early on. This is achieved by randomized "what-if" scenarios which support the user's understanding of the stochastic nature and of the resultant aggregated statistics. In this way, the tool provides assistance during the decision process for resource provision and allocation as well as contingency planning. Future studies are required to validate the findings of our tool.

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None to declare.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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