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Implementation of an Adaptable COVID-19 Utilization and Resource Visualization Engine (CURVE) to Depict In-Hospital Resource Forecasts Over Time

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Abstract

We developed an interactive web-based, decision support application that can adapt to the rapid pace of change in region-specific pandemic related variables and knowledge, thereby providing timely, accurate insights to inform a large healthcare system's proactive response to COVID-19 hospital resource planning. We designed the COVID-19 Utilization and Resource Visualization Engine (CURVE) app to be adaptable to real-time changes as the pandemic evolved, enabling decisions to be supported by contemporary local data and accurate predictive models. To demonstrate this flexibility, we sequentially implemented a Susceptible-Infected-Removed (SIR) model that incorporates social-distancing and imperfect detection (SIR-D2), an extended-state-space Bayesian SIR model (eSIR), and a time-series model (ARIMA). CURVE improves upon other pandemic forecasting solutions by providing adaptable decision support that generates locally calibrated forecasts aligned to health system specific data to guide COVID-19 pandemic planning. The app additionally enables systematic monitoring of forecast model performance and realignment that keeps pace with the pandemic's volatile spread and behavior. CURVE provides a flexible pandemic decision support framework that places the most accurate, locally relevant information in front of decision makers to enable health systems to be proactive and prepared.

Keywords: COVID-19, R Shiny, pandemic, forecasting, SIR model, ARIMA, resource utilization.

1. Background

The emergence of coronavirus disease 2019 (COVID-19) resulted in a global pandemic with significant morbidity and mortality (World Health Organization 2020, 2021; Zhu et al. 2020). As of July 16, 2021, there were 188,332,972 confirmed COVID-19 cases and 4,063,453 deaths reported worldwide (World Health Organization 2020). In the United States (US), COVID-19 has spread to all 55 jurisdictions with 33,797,400 total confirmed cases and 605,905 deaths (Centers for Disease Control and Prevention 2021; Johns Hopkins University & Medicine 2021). As COVID-19 continues to spread and case numbers rise, health systems have strained to keep pace with demands for hospital and critical care services, while managing potentially scarce resources (Moghadas et al. 2020). Therefore, the ability for health systems to predict increased utilization and proactively plan effective resource allocation, including when and how much to expand access to hospital beds, intensive care unit (ICU) beds and ventilators, (Emanuel et al. 2020; Grasselli et al. 2020) has become essential.

Many studies have utilized the basic susceptible-infected-removed (SIR) model to forecast how potential COVID-19 cases might impact the capacity of healthcare systems (Anastassopoulou et al. 2020; Binti Hamzah et al. 2020; Fanelli and Piazza 2020; Ferguson et al. 2020; Kermack and McKendrick 1927; Kucharski et al. 2020; Li et al. 2020; Massonnaud et al. 2020; Murray 2020; Predictive Healthcare at Penn Medicine 2020; Tsai TC 2020; Wu et al. 2020). These studies provide limited utility because they rely on models using national and international projections to provide insights for other countries, states, or regions and most do not: (a) take into consideration variation in infection and removal rates based on local population characteristics and geographic differences; (b) apply control measures or interventions from local healthcare systems and governments; or (c) account for constantly changing local community resource availability such as virtual and field hospitals (Atrium Health 2020). Additionally, despite their widespread application in the COVID-19 pandemic, basic SIR models were not developed to forecast hospitalizations, resulting in uncertainty about their accuracy (Murray 2020).

In response to the need for actionable data insights to guide proactive pandemic responses, we developed a web-based application, or 'app', that embeds COVID-19 forecasting models and uses local data to provide decision support. The COVID-19 Utilization and Resource Visualization Engine (CURVE) app provides health system leaders access to forecast predictions and near real-time observed hospital resources, such as, hospital beds, ICU beds, and mechanical ventilators, alongside contemporary estimates of existing and planned surge capacity. Here, we present our decision support app as a framework that can be deployed to provide relevant, timely insights to inform proactive planning for the current and future pandemics.

2. Methods

2.1. Study context and setting

Atrium Health is a large, vertically integrated, not-for-profit healthcare system with over 50 hospitals and 900 care locations in North Carolina, South Carolina, and Georgia. The health system is headquartered in Charlotte, North Carolina, the largest metropolitan region in the Carolinas. In response to the COVID-19 pandemic, Atrium Health activated its Corporate Incident Command (CIC) structure on March 6, 2020, three days after the first case of COVID-19 was reported in North Carolina and five days before Atrium Health diagnosed its first case of COVID-19. The primary goal of the CIC is to coordinate resource planning, preparedness, and decision making, while maintaining regular clinical operations, and protecting patients and staff. To effectively achieve this goal, the CIC leaders required real-time data insights into current and predicted hospital resource utilization.

The development and deployment of the CURVE app was designed for the greater Charlotte region that includes Anson, Cabarrus, Catawba, Cleveland, Gaston, Iredell, Lincoln, Mecklenburg, Rowan, Stanly and Union counties. The population of this region is around 2.5 million. App creation was divided into two phases. The first phase required the development of COVID-19 infection prevalence forecast modeling (Turk et al. 2020). The second phase involved user interface construction, emphasizing information accessibility to health system leaders, and configuration with the host server.

We collected bed capacity information from Atrium Health's electronic healthcare records (EHR), as well as daily counts of COVID-19 patients in the ICU, and on ventilators. Unique occupied beds were defined as an occupied bed in a calendar day regardless of the number of patients that used the bed during the day. Unique beds were derived from the hospital, nursing location, room number, and bed number. No restrictions were placed (e.g., department type, observation encounter) on the calculation of total occupied beds per day. App development was guided by a broad group of stakeholders including executive leadership, Information and Analytics Services leaders, and clinical experts. Stakeholder feedback guided the development team to focus CURVE's user interface on projected hospital and ICU bed use and capacity, along with ventilator use and capacity over time.

2.2. Phase I—forecasting model development

To forecast demand for in-hospital resources during the COVID-19 pandemic, it is important to accurately estimate the daily hospital "census" days or weeks ahead. In this paper, the COVID-19 hospital census is the daily aggregate number of beds occupied by COVID-19 patients at midnight across the subset of 11 Atrium Health hospitals in the greater Charlotte region, plus a virtual hospital (Atrium Health Hospital at Home). The virtual hospital uses telemedicine to treat patients who require only a minimal level of care. Early in the pandemic, limited hospitalization data meant that time series models could not be used directly, so health systems had to rely on epidemiological models that were then adapted to also "predict" hospital resources (for example, see Predictive Healthcare Team, P. M. (2020)). Adopting the same approach, we first deployed a conventional epidemic SIR model where, for a given time, S is the number of individuals that are susceptible to infection in the population, I is the number of individuals that are infected, and R is the number of individuals that are removed from the population via recovery or death from infection.

As the pandemic progressed and mitigation policies gained traction, the predictive performance of the SIR model declined. Hence, we deployed a more refined model that incorporated the effect of social distancing and imperfect detection (SIR-D2, deployed 4/11/2020). The theoretical details of this SIR-D2 model are well-detailed by Turk et al. (2020) for the interested reader. As the pandemic progressed and its behavior became more dynamic, we later deployed a Bayesian Hidden Markov Model based on SIR dynamics with a time-varying force of infection consistent with the epidemiology and reality of the evolving situation in our region. This latter extended-state-space SIR model (eSIR, deployed 4/25/2020) predicted time-varying population proportions of susceptible, infected, and removed components using Markov Chain Monte Carlo methods to collect draws from the posterior distributions for calculating estimates, conducting inference, and generating credible intervals for the unknown parameters. Because this model also has a time-varying infection rate, it is quite tractable with respect to accommodating dynamic pandemic behavior. As before, the interested reader can refer to Wang (2020) for more details.

In the case of the three SIR-type models, a time series of infection prevalence predictions was produced. Note these models merely served as an engine to generate "input" into the app early in the pandemic when there was little data. This approach allows for flexibility for the user to try their own model. Infection prevalence predictions were then passed on to the main engine of the app to deterministically derive time series for hospital metrics. Specifically, using assumptions based on scientific expertise, published experience in other countries, and statistical arguments, the subsequent steps were taken.

First, the user sets the proportion of COVID-19 cases that require hospitalization. In conjunction with a standard binomial argument and an assumed average illness duration of 14 days, a hospitalization admission rate (per person per day) can be determined. The infection prevalence predictions are multiplied by the hospitalization admission rate, the market share proportion, and the survivor proportion to generate daily hospital admissions, with the latter two factors being user-defined. Market share proportion is the proportion of the general population in the area thought to be served by the health system, while the survivor proportion is the complement of the proportion of admitted COVID-19 patients that will be lost due to mortality. Once the daily hospital admissions are determined, and the user defines the length of stay, we can determine the daily hospital COVID-19 census.

Then, using inputs for the proportion of COVID-19 patients in the ICU, proportion of ICU COVID-19 patients on ventilators, and corresponding length of stays, the adjusted daily censuses (for death and recovery) for COVID-19 patients in the ICU and on ventilators are derived.

Lastly, we developed an autoregressive integrated moving average (ARIMA; deployed 5/23/2020) model to improve predictive performance of hospitalizations as the pandemic evolution became increasingly erratic, more data became available for direct stochastic modeling, and the correlation between infection prevalence and hospital census became weaker. Leveraging an ARIMA model allowed us to shift away from the requirement of using input from the SIR–type models in the initial stages of the deterministic approach and to sunset these latter models. The ARIMA model is controlled by three meta-parameters: order of the autoregressive process, degree of differencing involved, and order of the moving average process (Hyndman and Athanasopoulos 2018). CURVE utilizes an algorithm due to Hyndman and Khandakar (2008) that returns the best ARIMA model according to an information criterion, such as Akaike's Information Criterion (AIC). The algorithm conducts a search over possible models within order constraints provided.

2.3. Phase II— user interface construction and CURVE app development

We developed the interactive CURVE app using R Shiny (RStudio, PBC 2020) with the schematic of the reactivity diagram as shown in Figure 1. The app contains four main parts— `mod_fun.R`, `global.R`, `ui.R`, and `server.R` files. The `global.R` file serves as an initiation placeholder for importing and wrangling data, and declaring global variables and default parameters. This file enables data such as model results (e.g., infection prevalence), default settings, parameters, current bed and ventilator counts, surge beds and additional ventilators, days for preparing additional resources, and stored records in a Comma Separated Values (csv) file to easily be modified without hard coding in the app. Then, `global.R` feeds the default values and parameters to the input components, followed by calling `mod_fun.R` to calculate the forecasted numbers, such as initial hospital census, incidence, and new admissions. The generated initial dataset is pushed into a main data hub as a `reactiveValues` object that can notify any reactive functions that depend on it. The reactive functions configure outputs that update the tables, charts, and plots the user sees. When users change input values, an `observeEvent` object is triggered; this pushes the changes to a `reactive` object for configuration, and then updates the main dataset via the `mod_fun.R` file. Finally, the main data in the `reactiveValues` object is altered, followed by a series of updating processes that cascade modifications throughout all outputs.

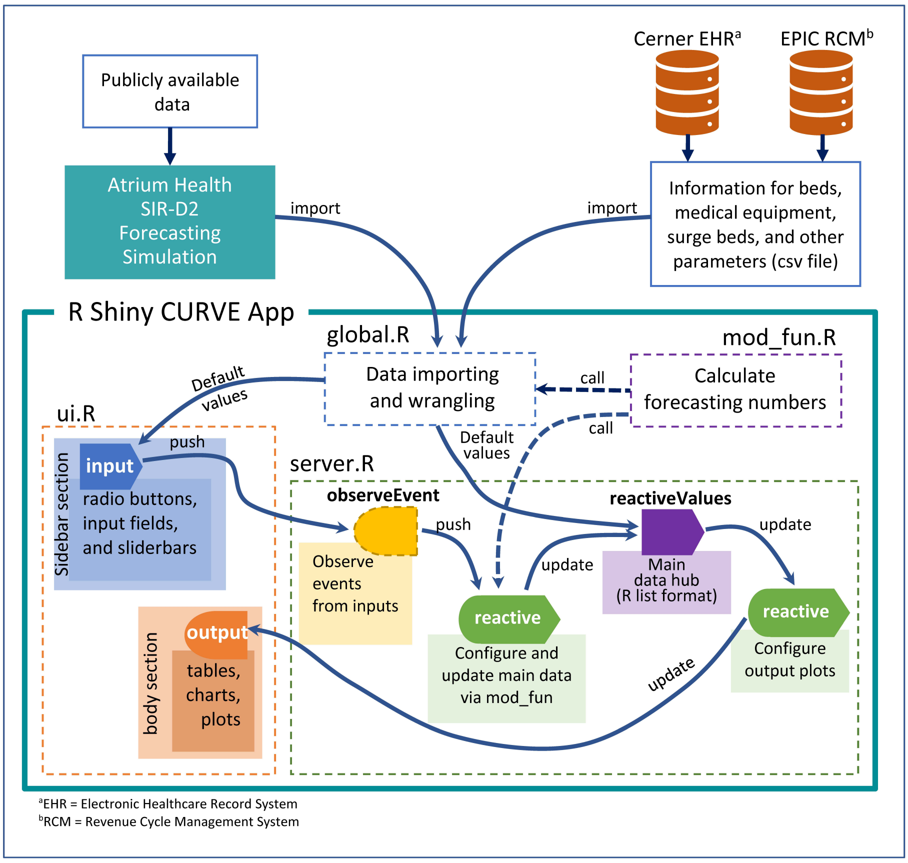

Figure 1: Schematic of the proposed CURVE app R Shiny reactivity diagram

Dynamically changing input parameters cause results to cascade through the following charts: 1) hospital census by day which shows the projected number of COVID-19 patients in the hospital; 2) the forecasted hospital census against capacity by day, including additional surge beds, to indicate if forecasted hospitalization requirements will exceed the health system's capacity; 3) the observed ICU proportion of hospitalization and observed mechanical ventilator occupancy status with 95% confidence intervals; 4) new daily admissions; and 5) the observed hospital census against the projected hospital census (Figure 2).

During the early weeks of the pandemic when very little was known about COVID-19, we constructed three scenarios (best-, moderate-, and worst-case) with corresponding settings to show a range of potential impacts on the hospital system and account for the uncertain nature of the COVID-19 pandemic (Table 1). We adjusted inputs (e.g., hospitalization rate) for scenario-based forecasting using estimates taken from the

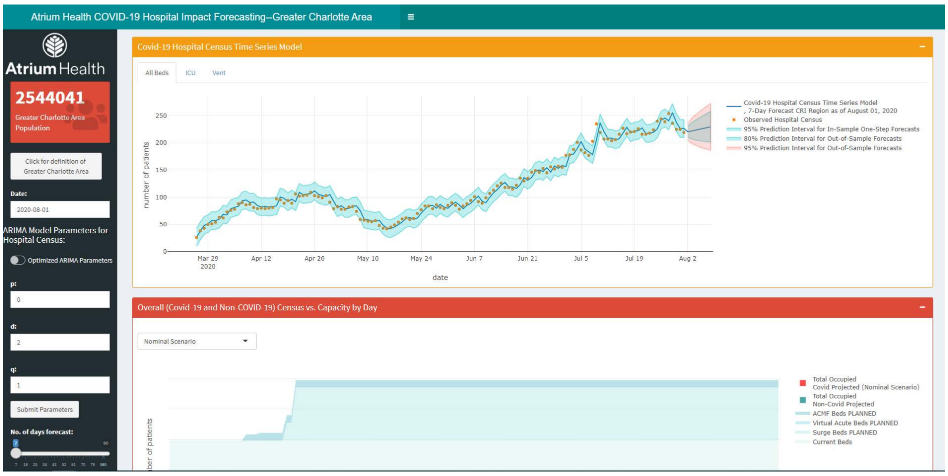

Figure 2: The output of the CURVE app deployed on 5/23/2020 and updated on 8/1/2020.

most recent scientific literature, and local data once we accumulated enough patients (Ferguson et al. 2020; Murray 2020; Verity et al. 2020).

Table 1: Parameter settings across different scenarios during the early stage of the pandemic.

	Scenario		
Parameter	Best-Case	Moderate-Case	Worst-Case
Hospitalization (% of Infections)	3	6	10
ICU(% of Hospitalization)	40	40	40
On Ventilator (% of ICU)	70	70	70
Average Hospital Length of Stay (Days)	7	7	7
Average Days in ICU	9	9	9
Average Days on Ventilator	10	10	10

3. Discussion

We present an adaptable decision support app that generates locally calibrated forecasts with health system specific data to guide COVID-19 pandemic planning. The CURVE app provides information based upon local infection patterns and allows for frequent updates as new data or models become available. In addition to providing decision support for health system leaders, the CURVE app provides development teams real-time insights for monitoring forecast model performance in the context of local resources. A publicly available copy of CURVE along with basic instructions for installation and usage is provided on GitHub (`https://github.com/philturk/CURVE`) with the most recent ARIMA model deployment.

The volatility of the pandemic's spread and behavior highlights the need for forecasting apps that are constantly monitored and easily adaptable to changing situations. For example, hospitalizations for COVID-19 patients significantly flattened after April 6, 2020, and the forecast trajectory for hospital census shifted from the moderate- to the best-case scenario under the SIR-D2 model (Figure 3). This local flattening of the hospitalization curve, which was likely in response to social distancing measures enacted in the last weeks of March, was immediately apparent in the CURVE app because we used local data with frequent recalibration to local trends. Because the CURVE app had previously demonstrated good model fit for the moderate-scenario parameter settings in near-real-time, health system leaders could visualize the significant flattening of hospitalizations after April 6, 2020. This sustained shift also served as an early warning to the modeling team that a new model may be needed maintain accurate forecasts. The forecast helped play into decision making around surge bed and staffing planning early in the pandemic, and then later helped guide the safe, methodical resumption of health system patient care activities.

While there are many apps that show the results of models, here we also demonstrate the importance of systematically monitoring model performance. We found that a model that performed well in the early stage of the pandemic began to perform more poorly as the pandemic progressed. This happened again after we fit the eSIR model, which initially had good performance that declined over time. As more data became available and direct time series modeling became an option, we fitted an ARIMA model to each of the hospital, ICU, and ventilator censuses. The ARIMA model performed far better compared to the derived SIR-based approaches, as shown by comparing Figures 2 and 3, and ultimately provided a very good fit to the data, which continues today. Staying the course with the original model and not adjusting to the significant "on the ground" changes happening with the pandemic would have led to erroneous insights and poorly informed decisions. It is likely that more sophisticated models (e.g., Seasonal Autoregressive Integrated Moving Average (SARIMA) or the Prophet forecast model developed by Facebook (Facebook Open Source 2020) may have to be considered as the pandemic behavior continues to evolve. The CURVE app allows for these more advanced models to be easily integrated and deployed on the backend, while preserving an easy-to-read interface for users on the frontend.

There are some limitations that should be noted. First, although the CURVE app was developed for health systems to insert local data using either csv files or through direct connection to their enterprise data warehouse, app developers still require R and R Shiny proficiency to modify the app or to add tables, charts, or graphs to the dashboard. Second, in order to provide reliable, locally relevant forecasts, app developers must have access to local data and modeling expertise to perform frequent model recalibration informed by local context. If such changes are not monitored and accounted for, projections could be taken out of context, leading to erroneous conclusions.

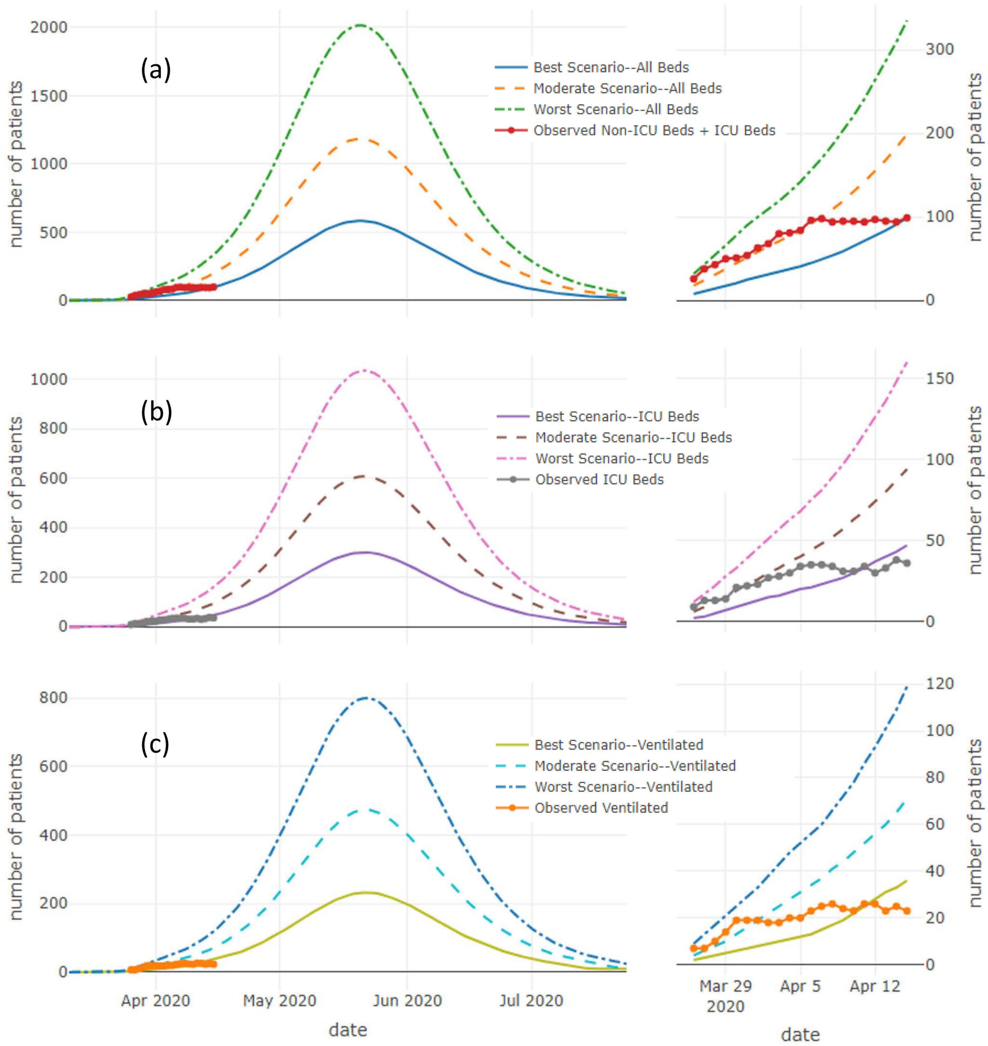

Figure 3: SIR-D2 model in (a) all beds, (b) ICU beds, and (c) ventilator census with best-case scenario, moderate-case scenario, and worst-case scenario settings. All graphs on right hand side are zoomed in results between Mar 26 and Apr 15, 2020.

4. Conclusion

Our interactive app provides locally relevant, dynamic, and timely information to guide health system decision making and pandemic preparedness. App frameworks like this will become increasingly important as health systems seek to proactively respond to current and future pandemics, and best serve their communities using data-informed strategies.

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