Design and Performance of a COVID-19 Hospital Recovery Model

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Objective: To determine the accuracy of a predictive model for inpatient occupancy that was implemented at a large New England hospital to aid hospital recovery planning from the COVID-19 surge.

Background: During recovery from COVID surges, hospitals must plan for multiple patient populations vying for inpatient capacity, so that they maintain access for emergency department (ED) patients while enabling time-sensitive scheduled procedures to go forward. To guide pandemic recovery planning, we implemented a model to predict hospital occupancy for COVID and non-COVID patients.

Methods: At a quaternary care hospital in New England, we included hospitalizations from March 10 to July 12, 2020 and subdivided them into COVID, non-COVID nonscheduled (NCNS), and non-COVID scheduled operating room (OR) hospitalizations. For the recovery period from May 25 to July 12, the model made daily hospital occupancy predictions for each population. The primary outcome was the daily mean absolute percentage occupancy error (MAPE) and mean absolute error (MAE) when comparing the predicted versus actual occupancy.

Results: There were 444 COVID, 5637 NCNS, and 1218 non-COVID scheduled OR hospitalizations during the recovery period. For all populations, the MAPE and MAE for total occupancy were 2.8% or 22.3 hospitalizations per day; for general care, 2.6% or 17.8 hospitalizations per day; and for intensive care unit, 9.7% or 11.0 hospitalizations per day.

Conclusions: The model was accurate in predicting hospital occupancy during the recovery period. Such models may aid hospital recovery planning so that enough capacity is maintained to care for ED hospitalizations while ensuring scheduled procedures can efficiently return.

INTRODUCTION

The COVID-19 pandemic presented hospitals with unprecedented rapid change. Hospital leadership and incident commanders are responsible for stewarding space, staff, and equipment to accommodate evolving patient needs during a crisis. This includes repurposing licensed beds and establishing new nonlicensed surge units.1 During the surge period, hospitals made changes to meet the rising COVID demand while non-COVID patient populations precipitously declined due to attrition in emergency department (ED) visits and, under the direction of State governments, suspension of scheduled admissions for elective procedures, including those from the operating room (OR).2,3

As a result, hospitals developed a backlog of patients who had avoided ED visitation or had their scheduled procedures deferred.4 During recovery from the surge, hospitals faced important decisions about whether and when to return licensed beds back to their original purposes, close surge units, and ramp up deferred procedural volume. They had to ensure that there was enough capacity available for multiple patient populations vying for inpatient space.

If hospitals did not carefully balance the needs of these populations in their recovery planning efforts, they risked blocking access to beds for patients arriving in the ED with urgent hospitalization needs or further deferring time-sensitive scheduled procedures. Many hospitals and health systems were flying blindly as they did not have data on the expected future demand of these patient populations.4 This lack of transparency created uncertainty and hindered effective recovery.

In contrast, a data-driven model that projects future hospital demand could create transparency into future capacity needs and thereby guide decisions about whether and when to close or repurpose surge spaces. To our knowledge, there have been no reports of such a framework and data-driven model.

We designed and implemented a data-driven model to project future hospitalizations during the recovery period at a large New England hospital. We measured the accuracy of the projected occupancy relative to actual occupancy over a 2-month period.

METHODS

The hospital’s Institutional Review Board Human Research Committee reviewed and approved access to EMR data for the purposes of this study. The need for oral or written consent from study participants was waived by the committee because data were deidentified and stored in secure, encrypted computers.

Study Setting and Population

This study was conducted at a 1034-bed quaternary care urban teaching hospital in New England. We defined the study
period as March 10 to July 12, 2020. The study period was composed of 2 phases: COVID Surge from March 10 to May 24 and Recovery from May 25 to July 12. The COVID Surge was defined as beginning from the date of the first admission for a patient with a COVID positive test and included the peak COVID inpatient occupancy; Recovery was defined as beginning approximately when the hospital began to implement recovery plans in conjunction with executive orders from our state’s governor lifting suspensions on elective procedures and ending when all nonlicensed surge spaces and repurposed licensed beds were converted back to their original uses and hospital procedural volume had returned to pre-COVID levels.

We included adult medical and surgical patients who were admitted during the study period to the hospital as inpatients. We excluded patients who were admitted to the Newborn service, admitted under observation status, and scheduled non-OR admissions, as we did not have data available for this population at the time of model creation.

We defined a patient as COVID if they had a single confirmed COVID positive PCR test during their hospital encounter or if they had presumed COVID due to clinical presentation despite a lack of positive PCR test as determined by the hospital’s bio-threats infection control specialists. We defined a patient as non-COVID if they met study inclusion criteria and did not meet the COVID definition criteria.

Figure 1 depicts the breakdown of hospitalizations into subpopulations that were projected by the model. We subdivided the non-COVID population into 2 subpopulations based on their admission source: scheduled OR and nonscheduled patients. Scheduled OR patients were defined as those whose hospital admission type was marked as elective and were admitted to the hospital after their surgical procedure. Nonscheduled patients were defined as those whose hospital admission type was marked as emergency, urgent, trauma, or other. These comprised patients admitted from the ED or from a referring acute care hospital.

Data Source
We obtained clinical and administrative data about hospitalizations from an institutional database linked to the patient’s electronic medical record that was updated nightly. This included patient demographics, hospitalization information, and clinical information regarding testing status.

Model Design and Development
The goal of the model was to provide projections of COVID and non-COVID inpatient occupancy to guide hospital planning efforts during the Recovery Period. The model was built at the request of clinical and operational leadership of the hospital’s COVID-19 Hospital Incident Command System (HICS). Model results were presented to HICS leadership three times per week. Results were used to guide discussions on whether nonlicensed surge units (eg, postanesthesia care units [PACUs] that had converted to COVID intensive care units [ICUs]) should be kept open or closed and whether repurposed licensed surge units (eg, surgical general care units that had converted to COVID medicine units) should be returned to their pre-Surge functions. The model output was not used to determine whether scheduled cases should be canceled. Rather, the future OR case schedule was used as a model input, as described below.

The model provided 1-week projections of inpatient occupancy for COVID, non-COVID nonscheduled (NCNS), and non-COVID scheduled OR patients. We used 1 week increments because this provided adequate lead-time for planning committees to adjust bed capacity allocation.

COVID Occupancy Projection
COVID occupancy projections were made using a simulation model that has 2 main components: one that estimates the number of daily COVID hospital admissions, and a second one that computes the occupancy projections. The latter combines projections for current COVID hospitalizations and the output of the former to project future COVID hospitalizations that had not yet occurred. The simulation was run for the future 7-day period and for a total of 50 iterations. The median estimated daily occupancy was reported.

Current Hospitalizations
To estimate the remaining length of stay (LOS) of current hospitalizations (ie, patients who were not yet discharged at the
time of projection), we used a resampling method in which we matched these patients to a list of candidate hospitalizations of COVID patients who had already been discharged during the surge period. The match was based on finding prior completed hospitalizations whose general care and ICU LOS were greater than or equal to the current hospitalization and whose sequence of general care and ICU utilization was either equivalent to or a feasible extension of the current hospitalization. If a list of candidates existed, then a sampling procedure was performed where a single candidate hospitalization was randomly selected, and its general care and ICU LOS and utilization sequence were used to approximate the remaining portion of the hospitalization. If no candidates existed, then we estimated the general care and ICU LOS by conditionally sampling from a best fit log-normal distribution for general care LOS and exponential distribution ICU LOS. When simulating care paths, we assumed that patients in general care would remain in general care and patients in an ICU would ultimately return to general care with no future readmission to the ICU.

Future Hospitalizations

To project future hospitalizations, we ran a linear regression on the time series of the prior 3 weeks of COVID hospitalizations. The 3-week timeframe was selected based upon iterative experimentation with several time horizons and examining the plausibility of the projections. Our final selection of 3 weeks was based upon balancing the need to be sensitive to new emerging trends in hospitalizations with ensuring that the trend was stable and did not represent a transient change.

We then took the slope identified by the regression to project the daily new COVID hospitalizations for the following 7 days. For each new COVID hospitalization, we randomly sampled from previously discharged COVID patients to estimate the general care and ICU LOS and utilization sequence.

NCNS Occupancy Projection

NCNS occupancy projections were made using a linear regression model with maximum likelihood estimation based upon the occupancy time series from the previous 14 days. Similar to the COVID occupancy projection, we selected the timeframe of 14 days to balance the need to be sensitive to emerging trends in hospitalizations with ensuring that the trend for this particular subpopulation was stable. This process was done separately for total occupancy, general care occupancy, and ICU occupancy. As with the COVID occupancy projection, the model was run for the future 7-day period and the estimated daily occupancy was reported.

Non-COVID Scheduled OR Occupancy Projection

Similar to the model used for COVID occupancy projections, non-COVID scheduled OR occupancy projections were made by combining projections for current and future hospitalizations. For each week during the recovery period, a simulation was run for these two populations. Future hospitalizations were based upon the 1-week forward OR schedule known at the time that the model simulation was performed. The simulation was run for the 7-day future period and for a total of 50 iterations with the median estimated daily occupancy reported.

We used matching to simulate the general care and ICU utilization and LOS for scheduled OR patients. The matching was based upon historical patients (hospitalized from January 1, 2019 through February 29, 2020) with the same primary surgeon and procedure type. For those patients admitted but not yet discharged, an additional criterion was to match with patients whose LOS was at least as long as the currently admitted patient’s LOS.

Outcomes and Statistical Analysis

We evaluated model performance by comparing the inpatient occupancy projected by the model with actual occupancy. The primary outcome to measure model performance was the mean absolute percentage error (MAPE) and mean absolute error (MAE) when comparing the total hospital occupancy projected by the model to the actual total hospital occupancy. The MAPE was calculated by taking the absolute error of each daily projection, dividing by the actual occupancy, and then averaging this result over all projection days. The MAE was computed similarly, but without the conversion to percentages.

The secondary outcomes to measure model performance were the MAPE and MAE for each subpopulation of COVID, NCNS, and non-COVID scheduled OR.

All analyses were performed using R version 4.0.0. Maximum likelihood estimations for determining best fit log-normal and exponential distributions were performed using the R packages MASS and fitdistrplus.

RESULTS

During the entire period including Surge and Recovery, there were 18,577 COVID positive hospitalizations, 10,906 NCNS hospitalizations, and 3641 non-COVID scheduled OR hospitalizations.

Table 1 demonstrates characteristics of patients in the 3 subgroups of hospitalizations during the recovery period. COVID patients compared with nonscheduled non-COVID and non-COVID NCNS hospitalizations were highly similar, but without the conversion to percentages.

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|                         | COVID | NCNS | Non-COVID Scheduled OR |
|-------------------------|-------|------|------------------------|
| Total hospitalizations  | 444   | 5637 | 1218                   |
| Average age (std)       | 57.7 (20.0) | 56.2 (21.5) | 58.4 (17.8) |
| Sex (n, %)              | 182, 41.0% | 2826, 50.1% | 595, 48.9% |
| Female                  | 262, 59.0% | 2811, 49.9% | 623, 51.1% |
| Male                    | 182 (21.2) | 76 (10.9) | 3.7 (5.4) |
| Avg LOS (std)           | 189, 61.9% | 4693, 83.3% | 1000, 82.1% |
| ICU utilization (n, %)  | 169, 38.1% | 944, 16.7% | 218, 17.9% |
| No                      | 417, 93.9% | 5460, 96.9% | 3, 99.8% |
| Yes                     | 27, 6.1% | 177, 3.1% | 1215, 0.2% |
| Disposition (n, %)      | 62, 14.0% | 1437, 25.5% | 326, 26.8% |
| Home health/visiting nurse | 8, 1.8% | 43, 0.8% | 1, 0.1% |
| Facility hospice        | 4, 0.9% | 71, 1.3% | 1, 0.1% |
| Home hospice            | 56, 12.6% | 112, 2.0% | 4, 0.3% |
| Long-term acute care    | 107, 24.1% | 679, 12.0% | 70, 5.7% |
| Skilled nursing facility/rehab | 162, 36.5% | 2911, 51.6% | 810, 66.5% |
| Home or self care       | 27, 6.1% | 177, 3.1% | 3, 0.2% |
| Expired                 | 18, 4.1% | 207, 3.7% | 3, 0.2% |
| Oncology                | 15, 3.4% | 483, 8.6% | - |
| Cardiology/cardiac surgery | 23, 5.2% | 593, 10.5% | 115, 9.4% |
| General medicine        | 295, 66.4% | 2055, 36.5% | - |
| Neurology/neurosurgery  | 21, 4.7% | 481, 8.5% | 187, 15.4% |
| Obstetrics              | 23, 5.2% | 577, 10.2% | - |
| Other                   | 1, 0.2% | 5, 0.1% | - |
| Pediatrics              | 19, 4.3% | 263, 4.7% | - |
| Psychiatry              | 8, 1.8% | 110, 2.0% | - |
| Surgery                 | 34, 7.7% | 951, 16.9% | 916, 75.2% |
| Transplant              | 5, 1.1% | 119, 2.1% | - |

*All surgical services except cardiology and neurosurgery. Std indicates standard deviation.
non-COVID scheduled OR patients had: a longer average LOS (18.2 vs 7.6 and 3.1 days); higher morality (6.1% vs 3.1% and 0.2%); higher rate of disposition to skilled nursing facilities/rehab (24.1% vs 12.0% and 5.7%); and long-term acute care facilities (12.6% vs 2% and 0.3%).

Figure 2 demonstrates the acute hospital occupancy during the surge and recovery periods and, for the recovery period, the model’s projected total hospital occupancy each day for comparison. For general care and ICU, respectively, Figures 3 and 4 demonstrate the actual total COVID, NCNS, and non-COVID scheduled OR hospital occupancy each day. For comparison during the recovery period, the projected occupancy is shown.

Table 2 demonstrates the MAPE and MAE for all subpopulations combined and individually. The model performed best in estimating total hospital occupancy with a MAPE of 2.8% and general care occupancy with a MAPE of 2.6%. The model was less accurate in projecting ICU occupancy with a MAPE of 9.7%. Across all subpopulations of COVID, NCNS and non-COVID scheduled OR patients, the model tended to have lower MAPEs for general care compared with ICU.

**DISCUSSION**

Hospital recovery planning after a COVID surge is critical to ensure enough capacity is available for COVID and non-COVID hospitalizations while maximizing capacity for delayed procedures. At a large New England hospital, we designed and implemented a model to guide recovery planning by projecting hospital occupancy. The mean absolute percentage error in projected versus actual occupancy in the total population was 2.8%. Specifically, for general care the percentage error was 2.6% and for ICU it was 9.7%. To our knowledge, this model is the first reported in the literature to project inpatient occupancy during recovery and designed specifically to aid in COVID recovery planning efforts.

The secondary outcomes of this study were the mean error in each of the 3 subpopulations for general care and critical care. We observed a trend in which the ICU projections had a larger percentage error (from 12.8% to 34.5%) compared with the general care projections. The absolute error (from 2.3 to 10.1 patients on average) was small, however. There are several potential explanations for this. First, ICU projections are more sensitive to small differences in actual versus projected occupancy, because the total number of patients with critical care needs is lower. Second, ICU utilization and LOS may be different during the recovery period compared with the surge period due to the evolution of treatments and other aspects of care that may influence these parameters. If this was the case, then random sampling of admissions may not appropriately account for these changes. Although the study period was not long enough to firmly conclude whether such trends exist, these model parameters should be monitored closely over time and adjustments to assumptions and sampling methods should be made if differences exist.

At our hospital, we found that the projection model helped operational leaders match incremental changes in bed supply and demand in lockstep, avoiding serious consequences of both shortage and surplus during the recovery period. Model results were reported at the hospital’s daily Incident Command System (HICS) meetings, which included members of the modeling team and clinical and operational leadership of the hospital. The model’s projected balance of COVID and nonscheduled non-COVID occupancy were used to determine the appropriate timing and order in which surge spaces could be closed or returned to their pre-Surge functions. For example, initially during the recovery period, we found that the rise in non-COVID occupancy was projected to outstrip COVID decline. Using this information, the HICS team slowed the closure of nonlicensed surge spaces. Eventually, this pattern was projected to reverse, and the HICS team increased the pace of returning surge spaces to their original uses.

On May 18, 2020 (7 days before the beginning of our study period) the governor of our state ordered that hospitals may begin “elective” OR procedures. Hospitals were required to attest that while ramping up the OR schedule that they were able to maintain adequate capacity to care for ongoing COVID hospitalizations and potential surges in hospitalizations. Our modeling was helpful to ensuring that we could reasonably attest to the government’s requirement and enabled us to carefully make decisions about the timing of conversion of surge units back to their original purposes.

In addition, the HICS team used the model output to ensure that the capacity projected to be available after accounting for
COVID and NCNS occupancy was adequate for the anticipated hospitalizations from scheduled OR cases. To create the OR schedule during recovery, a procedural planning team proposed weekly schedules. The proposed schedule was provided to the modeling team, which generated projections regarding downstream inpatient occupancy. This analysis was used to determine if the inpatient capacity available net of COVID and nonscheduled non-COVID would be sufficient. If the analysis showed that the needs of scheduled OR patients would likely outstrip anticipated future supply of inpatient beds, further adjustments were made to ensure procedural patients could be safely accommodated.

An example of such an adjustment was illustrated by the shifting of PACU spaces during Recovery in our hospital. Several PACU spaces had been converted to ICU beds during the Surge. Based on schedules proposed by the procedural planning team, the model indicated a potential deficit in downstream general care surgical beds for the following week. Based on this modeling, the team decided to incrementally convert surge ICU beds in the PACU to general care surgical beds, rather than return those beds directly to traditional PACU use.

In addition to informing capacity plans, another important use of the model was to help prepare the hospital for upcoming
staffing changes. By being able to anticipate changes to surge spaces ahead of time, the hospital could prepare staff for redeployment from those locations back to their home care areas. In many cases, the ability to schedule deferred procedural cases was dependent upon timely redeployment of staff to their original care areas. For instance, many ambulatory nurse staff had been deployed to inpatient care settings during the Surge and these nurses needed to return to their ambulatory practices before we could reestablish ambulatory surgical care, which was critical to recovering procedural volume.

Ensuring a data-driven approach to recovery planning has benefits from the hospital system perspective as well. In the COVID era, hospital capacities are increasingly linked. If one hospital or health system underestimates its capacity needs, it may have to transfer urgent COVID and non-COVID hospitalizations to another hospital or health system. This can have significant consequences for the receiving hospital’s ability to care for patients. For example, procedural specialties may have to limit scheduled OR patients to ensure sufficient capacity for this added volume of nonscheduled patients that could have been accommodated elsewhere.

Notably, the inputs to our model such as ED admission rate, LOS, and ICU utilization are standard, easily accessible, and tracked by most hospitals. Thus, we believe that the model could be implemented at other hospitals and scaled within a health system and for multiple health systems within a region. Future studies should explore this generalizability and scale given that it could be beneficial for hospital system and regional capacity planning.

| TABLE 2. Mean Daily Absolute Error and Absolute Percentage Error for Recovery Model Hospital Occupancy Projections |
|---------------------------------------------------|
| MAE | MAPE (%) |
|------|-----------|
| Total population | 22.3 | 2.8 |
| General care | 17.8 | 2.6 |
| ICU | 11.0 | 9.7 |
| COVID | | |
| General care | 6.4 | 10.0 |
| ICU | 5.1 | 34.5 |
| NONS | | |
| General care | 14.3 | 2.6 |
| ICU | 10.1 | 12.8 |
| Non-COVID scheduled OR | | |
| General care | 8.4 | 13.3 |
| ICU | 2.3 | 24.7 |

There were several important limitations to our approach. First, these data focus on projections from only 1 hospital and include a limited number of days of observations (constrained by the length of the pandemic recovery period). Additional work is required to ensure that the model reported in this study is generalizable to other hospitals. Although we believe that the data required to produce such models are obtainable and the populations included for projection are similar across most hospitals, a greater barrier to scaling this approach may be the availability of expertise to produce such models. In addition, non-OR scheduled admissions (ie, chemotherapy admissions) were not included as data on these hospitalizations were not prospectively available during model creation and implementation. Inclusion of this population will likely further improve model accuracy and performance.

**CONCLUSION**

The model was accurate in projecting hospital occupancy for key patient populations during the recovery period. Such models could guide recovery planning among hospitals so that scheduled procedural volume can efficiently return while maintaining enough capacity to care for urgent COVID and non-COVID hospitalizations.

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