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Characterizing the Reallocation of Hospital Beds Before and During the COVID-19 Pandemic in the United States using a Random Forest Regressor

The COVID-19 pandemic continues to cause unprecedented stress on hospitals. Despite available vaccines, COVID-19 continues to surge across the United States and hospitals need to anticipate these surges to ensure they have enough resources: physicians, surgeons, nurses, janitorial staff, beds, other medical supplies and equipment, and even entire buildings (Supady, 2021; Emanual, Persad, Upshur, Thome, Parker, Glickman, Zhang, Boyle, Smith, & Phillips, 2020; Callander & McInnes, 2020; Gessler, et al., 2021). For instance, in April 2020, the Commonwealth of Massachusetts reopened a Boston Medical Center facility to provide care to unhoused patients recovering from COVID-19 due to resource shortages (Komaromy & Tomanovich, 2020).

Understanding the extent to which hospitals have reallocated resources—particularly beds—from other healthcare units before and during COVID-19 can help predict future COVID-19 surges—as well as RSV and flu surges—and give insight into hospital resource management, adding to Pfeffer and Salancik's Resource Dependency Theory. Using Johns Hopkins's state-level COVID severity measures (cases and deaths) paired with the American Hospital Association's annual survey data (2018 through 2020), this study aims to characterize the reallocation of hospital beds in order to predict resource needs for U.S. hospitals for upcoming COVID-19 surges and future epidemics with a Random Forest Regressor (RFR).

Literature Review

Hospital Resource Management and Resource Dependency Theory

Rationing medical resources does not occur simply during times of crisis: staff are redistributed to different healthcare units, hospitals, counties, and states (Allen, 2014; Supady, 2021). For instance, obstetrics beds can become burn care beds, and more (Supady, 2021; Emanual, Persad, Upshur, Thome, Parker, Glickman, Zhang, Boyle, Smith, & Phillips, 2020; Allen, 2014). The COVID-19 pandemic has simply exacerbated this consistent resource dependency.

Resource Dependency Theory is an organizational sociological theory that attempts to explain how organizations interact with their environments to procure, sustain, and allocate resources. Organizations, such as hospitals, are not able to consistently produce all the resources they need to operate, which forces them to negotiate to acquire the resources they need to continue operating (Pfeffer & Salancik, 2003). For example, hospitals cannot consistently acquire enough ventilators, which forces them to negotiate with suppliers, other hospitals, and even the government to continue providing healthcare (Pfeffer & Salancik, 2003). For an organization to survive, it must be able to acquire and maintain resources. For a given hospital to survive a global pandemic, it must be able to acquire and maintain resources; if a hospital has a surfeit of burn care beds, for instance, but a dearth of cardiac intensive care beds, those burn care beds can be repurposed. According to Resource Dependency Theory, it is far easier to repurpose or convert resources than to acquire more, particularly when there is great competition for those resources (Pfeffer & Salancik, 2003).

Previous Studies

Previous studies have focused on how medical experts make triage decisions (Gessler et al., 2021), on quantifying the changes in hospital admission before and during COVID-19 (Rennert-May et al., 2021), and on quantifying the rate that hospital resources would be depleted depending on the effectiveness of public health measures (social distancing, mask wearing) (Barnett et al., 2020). Additional studies have addressed how detrimental the lack of access to healthcare—beds, medical specialists—is to overall mental health during a pandemic (Terraneo et al., 2021), and how lack of medical resources (beds, nurses, janitorial staff) lead to difficult triage decisions (Green & Armstrong, 1993; Allen, 2014).

COVID-19 triaging guidelines prioritize patients who have the highest probability of surviving and benefiting from ICU treatment (i.e., those most likely to survive ventilation, those who work in healthcare or have children, those who are vaccinated for COVID-19) (Tutic, Krumpal, & Haiser, 2022; Supady, 2021). While this utilitarian approach may seem ethical and most in line with Resource Dependency Theory, those with lower socioeconomic statues and those who are less educated suffer from worse health and higher mortality, putting them at higher risk for serious disease due to COVID-19 (Supady, 2021). Physicians have recommended that there be no difference in allocating scarce resources between patients with COVID-19 and patients with other medical conditions (Emanual, Persad, Upshur, Thome, Parker, Glickamn, Zhang, Boyle, Smith, & Phillips, 2020). Characterizing how hospital resources, like beds, were used before and during the COVID-19 pandemic can give insight into hospital resource management.

Data and Methods

The American Hospital Association (AHA) Annual Survey includes over 6,200 hospitals for 2018 through 2020 and samples bed count (total and specific healthcare unit), employment status (physicians, nurses, trainees), inpatient facility days, surgical operations, gross square footage of the physical hospital, whether the hospital is the sole healthcare provider for the community, and more.

Participation is voluntary and not all questions require a response for the survey to be considered "complete"; this may be how the AHA reports a greater than 80% response rate. The AHA does not gather much COVID-19 data—in 2020, the survey began recording total adult ventilators at the start and end of the reporting period. To characterize reallocation of hospital beds before and during the pandemic, data from Johns Hopkins University supplements the AHA data. The Johns Hopkins Coronavirus Resource Center (CRC) is a continuously updated source of COVID-19 data. The center collects and analyzes data on cases, deaths, tests, hospitalizations, and vaccines.

Variables

The variables used in the models include employee vacancies and total employed, beds, COVID-19 daily case and death count, gross square feet, and operating rooms. The employee vacancies include the following: physicians and dentists (plus residents and interns), nurses (registered nurses, nursing home unit nurses, licensed practical (vocational) nurses, nursing assistive personnel), pharmacists (plus pharmacy technicians), technicians (pharmacy technicians, radiology technicians, laboratory technicians), respiratory therapists, and other trainees. The types of hospital beds used in the models are general medical and surgical (adult) beds, medical and surgical intensive care beds, cardiac intensive care beds, pediatric beds (general medical and surgical, intensive care), neonatal beds (intensive and intermediate care), obstetric care beds, burn care beds, physical rehabilitation care beds, alcohol/drug abuse or dependency inpatient care beds, psychiatric care beds, nursing beds (skilled, intermediate), long-term care beds (acute and other), as well as other special and intensive care beds.

Data Cleaning

Null values were imputed with the mean for the following variables: total employed, gross square feet, operating rooms, and staff vacancies.

Methods

The dependent variables, or target outcome, are the hospital bed counts by type. The independent variables, or features of the machine learning models, are employee vacancies, gross square feet, operating rooms, and COVID-19 case and death count. The Support Vector Regressor and Random Forest Regressor models will be evaluated, first, by their ability to converge, and second, by their accuracy scores.

Models

Support Vector Regressor

Using a Linear Support Vector Regressor from sci-kit, the model was trained with hospital employee vacancies, total employed, gross total square feet, operating rooms, and COVID-19 daily case and death count to predict bed count. The model failed to converge, which indicates that the data are not linearly separable.

Random Forest Regressor

Since the Support Vector Regressor failed to converge, I utilized a Random Forest Regressor, which is a non-linear model that aggregates the results of decision trees. Just like the SVR, the RFR was trained with hospital employee vacancies, total employed, gross total square feet, operating rooms, and COVID-19 daily case and death count to predict bed count. The model converged and can reasonably predict counts for certain bed types. The model can predict that a given hospital will have a given number of beds based on the input data.

Descriptive Statistics

Table 1: Descriptive Statistics of COVID-19 Case and Death Count (2020 and 2021)

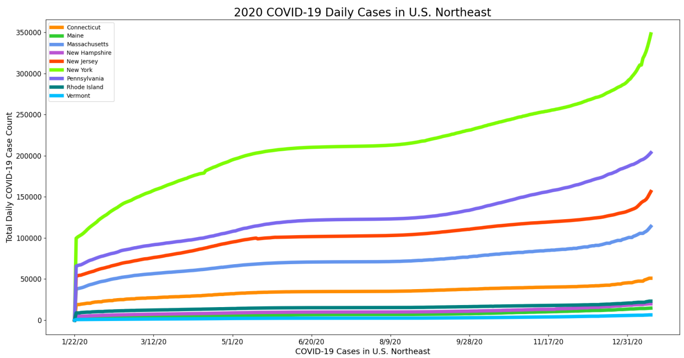
Year	Gross Square Feet	Total Personnel Vacancies	General and Medical Surgical (Adult) Beds	Medical and Surgical Intensive Care Beds	Cardiac Intensive Care Beds	Pediatric Care Beds	Pediatric Intensive Care Beds	Neonatal Intensive Care Beds	Neonatal Intermediate Beds	Obstetric Care Beds
2018	56.13 (± 193.48)	57.24 (± 131.35)	64.77 (± 95.30)	9.09 (± 14.61)	2.33 (± 8.05)	4.06 (± 17.48)	0.82 (± 4.77)	3.68 (± 12.42)	1.15 (± 5.67)	9.03 (± 16.04)
2019	61.35 (± 208.11)	61.27 (± 153.01)	64.22 (± 96.31)	9.00 (± 14.54)	2.37 (± 8.41)	3.95 (± 17.63)	0.84 (± 4.92)	3.68 (± 12.53)	1.14 (± 5.72)	8.87 (± 15.99)
2020	64.55 (± 228.69)	64.22 (± 155.68)	64.30 (± 98.17)	9.36 (± 15.57)	2.34 (± 8.39)	3.71 (± 17.03)	0.81 (± 4.84)	3.65 (± 12.56)	1.04 (± 4.97)	8.71 (± 16.01)

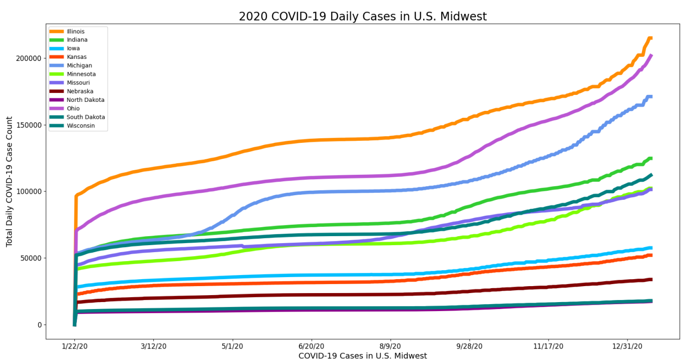
Table 2: Descriptive Statistics of Hospital Data (2018, 2019, and 2020)

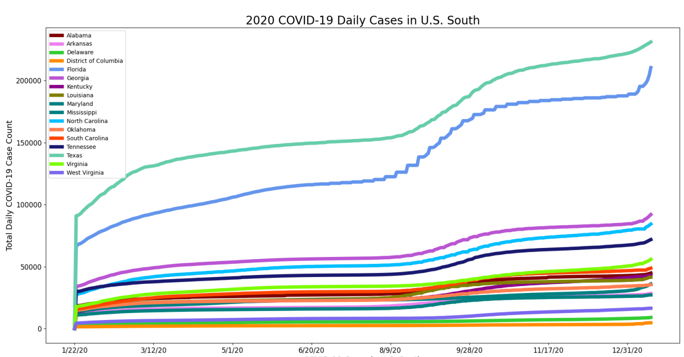
Year	Average COVID-19 Case Count	Total COVID-19 Death Count
2020	517,304.10 (± 2,034,329.00)	3,342.00
2021	189,134.80 (± 620,185.90)	3,342.00

Table 3: Descriptive Statistics Graphs of COVID-19 Case Count by U.S. Region (Northeast, Midwest, South, West, and U.S. Territories)

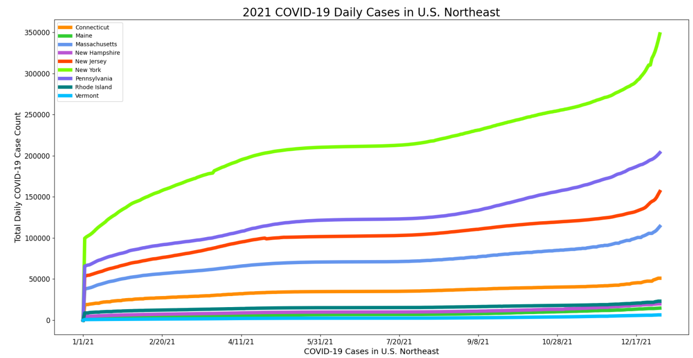
2020 COVID-19 Daily Case Count in U.S. Regions

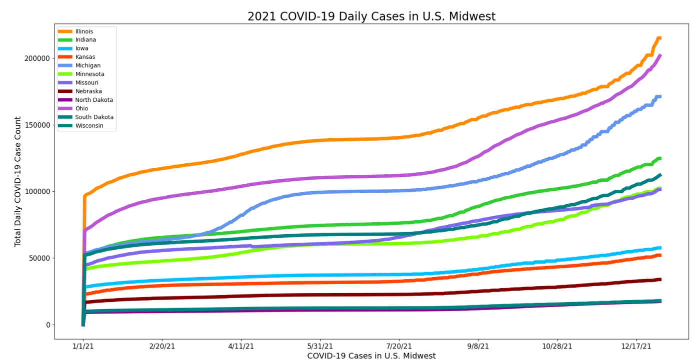


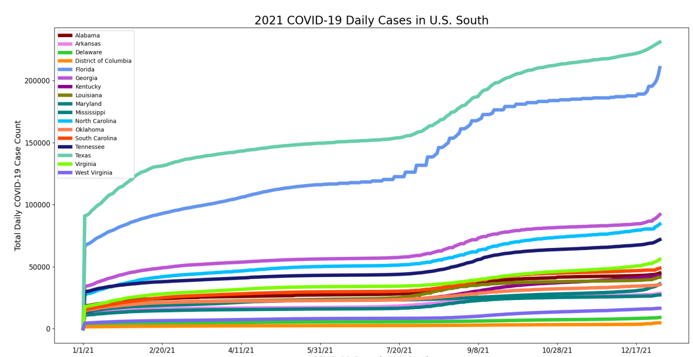




2021 COVID-19 Daily Case Count in U.S. Regions







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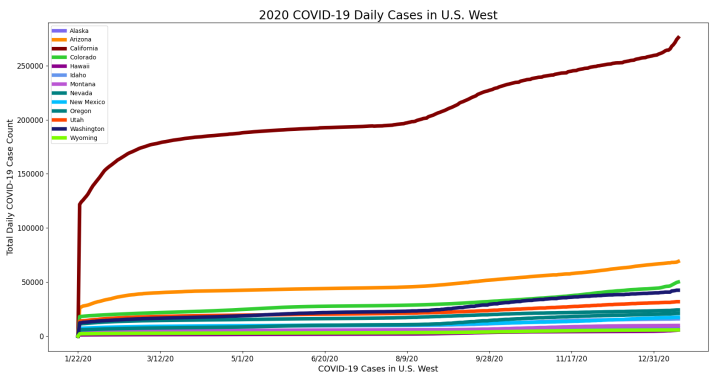
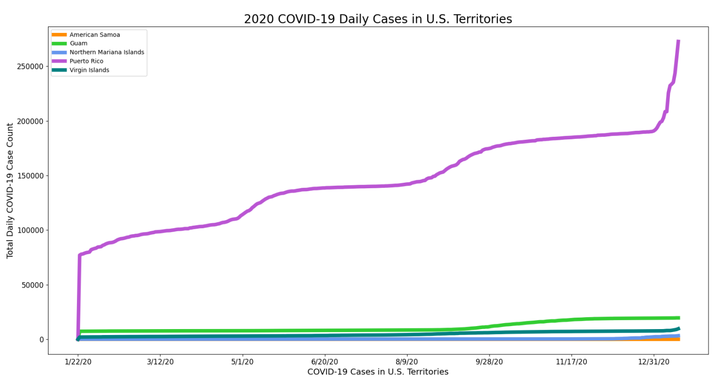
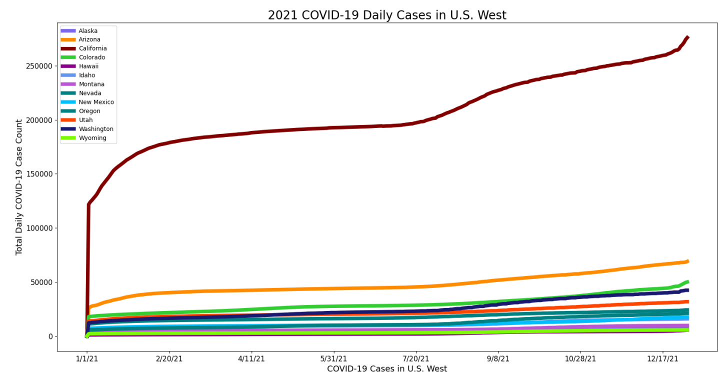
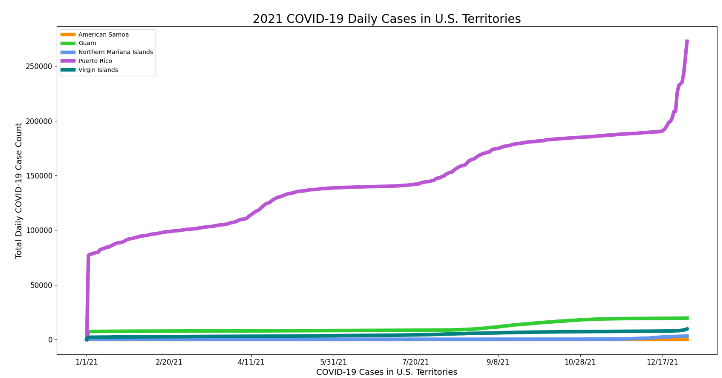




2021 COVID-19 Daily Case Count in U.S. Regions





Results

Bed Type	Random Forest Regressor Accuracy Score
General Medical and Surgical (Adult) Beds	93.98%
Medical and Surgical Intensive Care Beds	86.12%
Cardiac Intensive Care Beds	69.01%
General Medical and Surgical (Pediatric) Beds	73.01%
Pediatric Intensive Care Beds	62.92%
Neonatal Intensive Care Beds	71.16%
Neonatal Intermediate Care Beds	44.49%
Obstetric Care Beds	79.94%
Burn Care Beds	33.86%
Physical Rehabilitation Care Beds	60.38%
Alcohol/Drug Abuse or Dependency Inpatient Care Beds	35.96%
Psychiatric Care Beds	80.57%
Skilled Nursing Care Beds	73.32%
Intermediate Nursing Care Beds	-46.42%
Acute Long-Term Care Beds	62.09%
Other Long-Term Care Beds	52.74%
Other Special Care Beds	40.77%
Other Intensive Care Beds	36.06%
Other Care Beds	25.16%

The Random Forest Regressor has some high and low accuracy scores, meaning that the labels the model correctly predicted out of the total number of predictions varied, depending on bed type. The RFR accurately predicts the bed count for certain bed types: general medical and surgical (adult) beds and medical and surgical intensive care beds (both above 86%). The RFR relatively accurately predicts the bed count for others: general and medical surgical (pediatric) beds, neonatal intensive care beds, obstetric care beds, psychiatric care beds, and skilled nursing care beds (all above 70%). The RFR has a poor accuracy of predicting burn care bed count, alcohol/drug abuse or dependency inpatient care bed count, other intensive care beds, and other care beds (all below 40%). The RFR's worst accuracy is in predicting intermediate nursing care beds: -46.42%.

Conclusion

The Random Forest Regressor's accurate predictions of some beds is an introductory characterization of the extent to which hospitals have reallocated resources from other healthcare units. To predict future COVID-19 surges—as well as RSV and flu surges—and to extend Pfeffer and Salancik's Resource Dependency Theory, further analysis (with more extensive data) needs to be done, likely using the same model type or potentially a deep neural network.

Limitations and Future Research

The limitations to this study revolve around data accuracy and combining the two datasets: the American Hospital Association and Johns Hopkins' University. Since the American Hospital Association will not release their 2021 data until late December 2022, there is no 2021 data to include in this model. As such, COVID-19 vaccine and booster data cannot be used to supplement the models, because the vaccines were released in late December 2020. Moreover, the death count reports may be inaccurate (both 2020 and 2021 report 3,342 total deaths) in addition to being very small. If the data can be more accurate—or at least determined to be accurate—and more broad, future studies may likely be able to predict future pandemic and epidemic surges.

Resources

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