Deployment of an Interdisciplinary Predictive Analytics Task Force to Inform Hospital Operational Decision-Making During the COVID-19 Pandemic

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Abstract

In March 2020, our institution developed an interdisciplinary predictive analytics task force to provide coronavirus disease 2019 (COVID-19) hospital census forecasting to help clinical leaders understand the potential impacts on hospital operations. As the situation unfolded into a pandemic, our task force provided predictive insights through a structured set of visualizations and key messages that have helped the practice to anticipate and react to changing operational needs and opportunities. The framework shared here for the deployment of a COVID-19 predictive analytics task force could be adapted for effective implementation at other institutions to provide evidence-based messaging for operational decision-making. For hospitals without such a structure, immediate consideration may be warranted in light of the devastating COVID-19 third-wave which has arrived for winter 2020−2021.

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Before the onset of the coronavirus disease 2019 (COVID-19) pandemic in the United States, the American Hospital Association hosted a webinar in which a "best guess epidemiology" scenario suggested that COVID-19 cases could double every 7 to 10 days and lead to 5 million COVID-19 hospitalizations across the United States, while warning that hospitals should prepare for a health care burden 10 times worse than a severe flu season.[1] On the date of that webinar (February 26, 2020), there had been approximately 200 confirmed COVID-19 cases in the United States. By the following week, the United States confirmed case count had climbed to more than 1000, indicating an alarming potential for a quicker case doubling time (CDT) than the predicted 7 to 10 days.[2] This explosive early trajectory sparked a national discussion that the pandemic could soon overwhelm US health system capacities and pose a threat to the health and safety of both COVID-19 and non−COVID-19 hospitalized patients. At that time, this exact scenario was unfolding simultaneously across northern Italy, with overwhelmed hospitals reportedly housing patients on mattresses on the floor while struggling to provide basic services such as palliative care and child delivery.[3]

Health care institutions recognized an immediate need for evidence-based guidance to inform hospital operational decision-making and ensure the provision of high-quality COVID-19 and non−COVID-19 patient care throughout the unknown course of the impending pandemic. Here, we share

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the approach initiated at Mayo Clinic in early March to rapidly assemble and deploy an interdisciplinary, agile task force of academic, clinical, and hospital administrative experts to provide actionable prediction of the COVID-19 impacts on hospital census and operations.

FORMATION OF THE COVID-19 PREDICTIVE ANALYTICS TASK FORCE

Following Mayo Clinic's rich history of being a physician-lead matrix organization, the executive dean of practice funded the identification of a COVID-19 data governor group consisting of the chief value officer, division chair, health care policy research, and chair, quality, experience, and affordability. The first task of the three data governors was to develop an interdisciplinary predictive analytics task force. The interdisciplinary COVID-19 predictive analytics task force was conceived as a partnership between the physician, scientific, and administrative leadership of Mayo Clinic entities including Quality, Experience, and Affordability; the Department of Health Sciences Research; the Department of Data and Analytics, and the Robert D. and Patricia E. Kern Center for the Science of Health Care Delivery. Briefly, the mission of the Kern Center is to develop, analyze, and rapidly diffuse transformative health care solutions through partnership with the practice.[4] A three-person leadership group, the data governors, met to draft a concise mission statement and deliverable for the task force.

Their mission was to estimate the number of COVID-19 patients who will need hospitalization and intensive care unit (ICU) beds at each Mayo Clinic hospital as well as the time spent above hospital capacity. The deliverable goal was to provide ongoing COVID-19 predictive analytics reporting to hospital leadership across Mayo Clinic sites with key messages updated multiple times per week.

An economic impact analysis was not considered in-scope. The primary focus of this task force was to be able to predict capacity to help operational decision-making and to ensure safety of patients returning to campus. With a clear mission and deliverable defined, task force leadership strategically recruited members from multiple departments and roles to ensure diverse expertise across multiple scientific domains including infectious disease, health services research and policy, statistics, bioinformatics, digital health, epidemiology, and hospital operations, with strong representation from clinical and administrative leadership at each of the Mayo Clinic destination medical centers (DMCs) in Rochester, MN; Phoenix, AZ; and Jacksonville, FL (Table 1). During the first 2 months (March and April 2020), the task force meeting schedule consisted of daily 1-hour Zoom video conferences (Monday through Friday) with ad hoc weekend calls as necessary. An assigned project manager coordinated task force meeting agendas and key messages.

TASK FORCE ASSESSMENT OF EXTERNAL COVID-19 HOSPITAL USE PREDICTION MODELS

The first priority undertaken by the task force was to comprehensively identify and assess all external COVID-19 prediction models to gain an understanding of their methodologies and outputs. We evaluated approximately 15 publicly available models including those from the Institute for Health Metrics and Evaluation,[5] Qventus,[6] University of Basel,[7] Covid ActNow,[8] Youyang Gu,[9] and Cornell.[10] There were several similarities in the methodologies of these external models, with most relying on a generalized susceptible, exposed, infected, recovered framework.[11-13] However, there was significant variation across models regarding their inputs, assumptions, outputs, and applicability to the Mayo Clinic practice. For example, many models predicted COVID-19 cases at the state or county level, but were unable to account for local hospital-level inputs such as length of stay, total available medical and ICU beds, or intra-institutional patient transfer between regional hospitals.

As the task force continued to test external models, a solid conceptual understanding of the key variables and inputs

TABLE 1. Composition of Interdisciplinary Coronavirus Disease 2019 Predictive Analytics Task Force[a]

Pre–COVID-19 role at Mayo Clinic	Role on COVID-19 task force
Chair of Quality, Experience, and Affordability (Administrative Leader)	Serve as task force leadership by bringing team together, communicating vision and directives, and facilitating dissemination of analytics with hospital practice leadership.
Chief Value Officer (Physician Leader)	
Director of Research, Kern Center for the Science of Health Care Delivery (Scientist Leader)	
Project management	Set meeting cadence, assist with communication of key messages and drafting of report materials, and provide pre-meeting agendas and post-meeting summaries.
Faculty-level Subject Matter Experts with expertise in artificial, intelligence, natural language processing, biostatistics, digital health, epidemiology, and health policy/health services research	Assess predictive analytic methodologies, create automated visual data display/dashboards, review literature, and develop data-driven/evidence-based assumptions for inputs of predictive models.
Staff statisticians, data scientists, and analysts	Investigate external COVID-19 models for utility and adaptability to Mayo Clinic hospitals and investigate/compile reliable county-level data sources.
Chair, Department of Data and Analytics	Lead the development of COVID-19 testing and inpatient data mart.
Chair, Infection Prevention and Control	Lead surveillance of nosocomial infections and communicate PPE guidelines and best practices.
Infectious disease physicians	Provide expertise on infectious disease transmission.
Clinical practice leadership (MDs)	Provide expertise and frontline insight of COVID-19 issues/concerns voiced by the practice while critically reviewing deliverables and key messages for effective communication with the practice.

[a]COVID-19, coronavirus disease 2019; MD, medical doctor; PPE, personal protective equipment.

needed for predictive COVID-19 modeling specific to our hospital system was formed within the group. This was accomplished using rapid cycles of change within an agile framework. Key model inputs identified through this approach included community-level case doubling time, test positivity rate, hospitalization rate, and effectiveness of social distancing. Ultimately, the handful of external models which provided flexibility for end-users to input community- and hospital-specific parameters used small studies reliant on early Chinese data[14,15] to set default parameter values. The generalizability of these values to other hospitals was often unknown and it was not possible to refresh these values with real-time hospital- and community-specific data. Furthermore, for these tools to be operational for the practice, we needed to have high data availability, automation in the data curation and tabulation processes, and succinct visuals to convey the message at a time when both hospital staff and leadership were under extreme pressures. As such, the task force recognized a need for the development of an internal data framework to compile state-, county-, and hospital-level testing and case data so that we could update critical model assumptions on a daily basis with data relevant to each of our unique hospital regions.

DEVELOPMENT OF DASHBOARDS TO DISPLAY KEY INTERNAL AND EXTERNAL COVID-19 METRICS

Having recognized a need for real-time, region-specific COVID-19 data for each of our hospitals, the data scientists on our taskforce began compiling and automating an internal data framework which would be updated daily with state- and county-level case data using application programming interfaces from aggregated national COVID-19 data sources such as those provided by USA-FACTS[16] and the *The New York Times*.[17] From this data, digital scientists on the task force created red-yellow-green status visualizations of test positivity rates and CDTs at the state, county, and health referral region for each of our hospitals. This dashboard provided the task force with one central location containing high-level, near—real-time summary visualizations from which to quickly surveil key COVID-19 parameters in each of our hospital regions.

In parallel with the CDT and test positivity dashboards described above, several task force members engaged with Mayo Clinic Hospital Incident Command System leadership to create a daily dashboard displaying internal hospital-specific metrics such as total tests ordered, total positive tests and test positivity rate, current hospital and ICU COVID-19—positive census, and cumulative COVID-19 admissions and inpatient fatalities. This COVID-19 leadership dashboard used data captured by the electronic health record (EHR) and was updated nightly; it is conceptually similar to COVID-19 dashboards recently described by other institutions.[18,19]

CURATION OF A CENTRALIZED, EHR-BASED REAL-TIME COVID-19 DATA MART

As we began to internally disseminate the dashboards described above, many clinicians, administrative leaders, and researchers across Mayo Clinic began to express a need to access COVID-19 data for various clinical, operational, and research initiatives, resulting in a significant amount of task force time spent responding to queries and sharing knowledge about the current COVID-19 data framework that the task force had developed. To facilitate, centralize, and operationalize COVID-19 analytics, a distinct COVID-19 data mart was built by Mayo Clinic's Department of Data and Analytics to house formatted tables containing Mayo Clinic's COVID-19 lab testing, hospital and ICU census data, and critical supply information (eg, mechanical ventilator status). The data mart build was agile and customizable based on task force feedback, with separate tables built for polymerase chain reaction testing, serology testing, and inpatient COVID-19 data. Key variables included test date/times, test results (including all positive, negative, indeterminate, and repeat tests), demographics (age, race, ethnicity, county/state of home address), bed type (ICU versus medical/surgical), status of mechanical ventilator use, and admit/discharge dates. The resulting COVID-19 data mart went live during the first month and continues to undergo refinement with additional tables and more real-time data from the EHR. This data mart exists within our unified data platform and contains easily queryable (using structured querying language) COVID-19 data. In addition to providing key information to inform predictive modeling efforts, the data mart has shown extended utility and is being used by many of the ongoing surveillance and research efforts at our institution.

CREATION OF MAYO CLINIC HOSPITAL—SPECIFIC BAYESIAN PREDICTIVE COVID-19 CENSUS MODELS

The operationalization of the Mayo Clinic COVID-19 data mart provided reliable daily and real-time hospital and ICU census and test results. This resource, coupled with external COVID-19 data and metrics collated for the CDT and test positivity dashboard, made it possible to develop an internal predictive modeling solution through the application of machine learning by Mayo Clinic experts in Bayesian modeling. The internally developed model is a stochastic suspected, infected, recovered model[20] for each US county updated daily with case counts. The infection rate driving the suspected, infected, recovered model can vary across county and time in a space-time correlated manner via a log-Gaussian process. The hospitalization rate for the counties in our health referral regions is trended over time and space, informed by state-level data, and refined

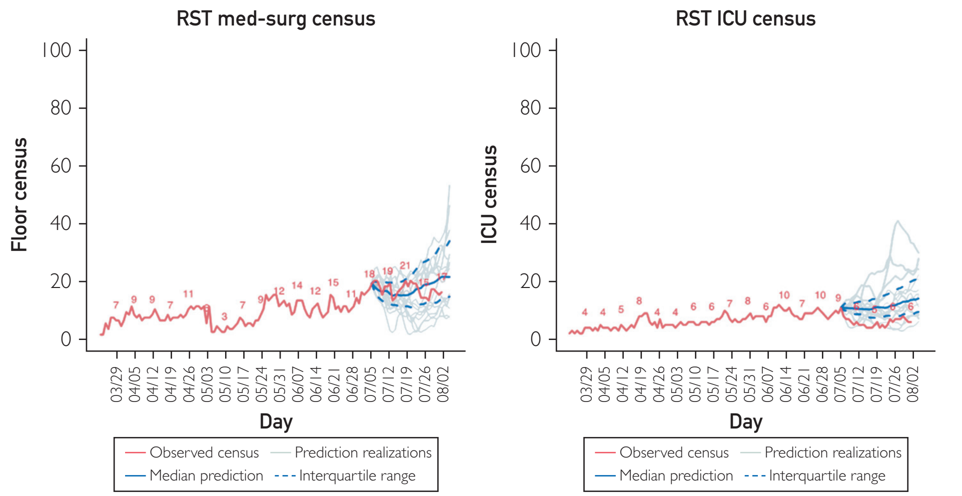

FIGURE 1. Four-week historical forecast and performance of internally developed Bayesian coronavirus disease 2019 (COVID-19) census model. The forecast for the hospital census at Mayo Clinic Rochester (RST) is broken up by floor and intensive care unit (ICU). Median predictions are represented in blue, whereas the actual observed data is red.

with Mayo Clinic site-specific data. Floor/ICU length of stay distributions are informed by macro data and refined with Mayo Clinic site-specific data. Currently our model incorporates all of the following data sources: 1) case/test volumes over time from all US counties; 2) state level admission data over time; 3) Mayo Clinic site-specific admission data over time; 4) Minnesota Department of Health county-level hospitalizations over time; 5) Mayo Clinic site-specific ICU/floor discharge/transfer data from all Mayo Clinic sites; 6) daily mobility/social proximity measures in each county calculated from cell phone data by Unacast[21]; and 7) dozens of studies from the literature to inform prior distributions. Predictions are made by simulating 500 possible futures (cases and hospitalizations) from the posterior distribution. Figure 1 shows a historical forecast from July 7, 2020, for hospital census at Mayo Clinic Rochester (floor and ICU) along with what actually happened for the next 4 weeks. The prediction distribution is represented in blue, while the actual observed data is in red. This modeling approach allowed our task force to provide more timely, flexible, and hospital-specific predictions compared with the external COVID-19 models we evaluated. For each of our hospitals, if the model predicted a greater than 30% chance of COVID-19 ICU census being greater than 50% of ICU bed capacity in the next 4 weeks, that hospital was given a red alert. If the model predicted that less than 10% of COVID-19 ICU census would be greater than 50% of ICU bed capacity in the next 4 weeks, that model was given a green status, while intermediate risks (10% to 30%) were given yellow warnings. A pre-formatted 20-slide PowerPoint presentation including alert levels, site-specific predictions, historical model accuracy summaries, and three to five brief key messages was e-mailed twice weekly to practice leadership at each of our hospitals.

EVOLUTION OF THE TASK FORCE FOR ADDITIONAL HOSPITAL MONITORING AND DELIVERABLES

While the primary mission of the task force was to provide predictions of hospital and ICU bed census across multiple Mayo Clinic hospitals, meetings were purposefully structured to allow time for open discussion of any relevant COVID-19 information that had been recently disseminated in the scientific literature or media. This democratic model of teamwork and communication is a well-established tradition of the Mayo Clinic practice,[22] and the extension of this model to our predictive analytics task force facilitated the development of additional important work discussed below focused on the safety of our staff and hospitalized non−COVID-19 patients.

Monitoring Usage and Availability of Personal Protective Equipment

Shortly after the pandemic began, personal protective equipment (PPE) became a central focus as a key consumable that was essential for the safety of patients and health care workers. The task force commissioned a subteam to model the PPE resources available to the institution. A two-pronged approach was taken for modeling PPE. First, the historical records maintained by institutional supply chain management were added to the COVID-19 data marts so that the data would be consumable by the applications. These data elements allowed for historical consumption rates to be tabulated for various face masks, gloves, eye protection, gowns, and other critical PPE stock. Next, detailed observational studies were initiated to empirically measure consumption rates for each PPE category per day, per patient, and per staff member. Finally, the estimated consumption rates were linked with model estimates to provide a prediction of how long current supplies would last based on projected volumes and inventory. As the pandemic continued, changes to PPE guidelines were factored into our modeling to update projected consumption.

Effectively messaging the predictions of supply on hand to the practice required pilot testing a variety of visuals. There was initial interest in having highly detailed counts, by site, of inventory, consumption, and time until critical shortages. However, because all Mayo Clinic sites work from a single inventory, a single dashboard was used to ensure an equitable distribution of PPE among all sites in the enterprise. Similar to the hospital and ICU COVID-19 census predictions, a simple red-yellow-green dashboard was created to convey status regarding the amount of supplies available (Figure 2). As the pandemic progressed, detailed accounting of the supplies on hand, predictions made, and errors in predictions were tabulated. The internal development team used this information to refine the prediction models and add the necessary automation to the system to ensure accurate predictions were available to leadership.

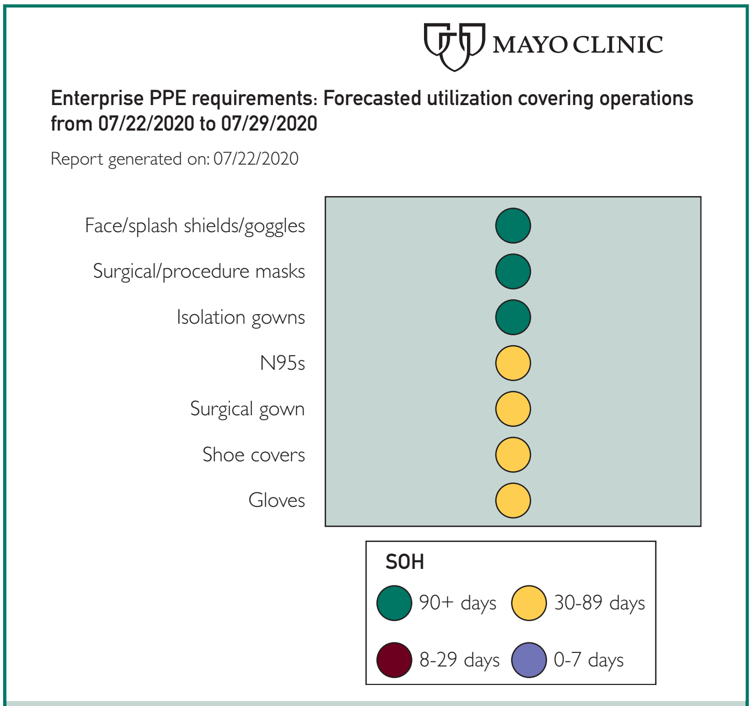

FIGURE 2. Weekly dashboard showing modeled personal protective equipment supply on-hand (SOH) at Mayo Clinic.

Safety for Hospitalized Non−COVID-19 Patients

With flattened pandemic curves in our DMC regions becoming evident from our modeling in April 2020, (consistently <10% of hospital beds being used for COVID-19 patients), our hospital and procedural practices cautiously prepared to increase provision of non−COVID-19 care. However, whether patients presenting for non−COVID-19 care would be at risk of contracting COVID-19 in our facilities was of concern. Therefore, leadership widened the task force's analytic scope to include monitoring patient safety related to COVID-19 by characterizing risk and rate of health care—associated infection in patients hospitalized for non-COVID indications at the three Mayo Clinic DMCs.[23]

Succession of Task Force Leadership and Steady-State COVID-19 Monitoring

As our task force evolved from its formation in March 2020 through several peaks and plateaus at various times across our different hospital regions as of December 2020, the consistency of our modeling efforts led to adoption of our summary reports by hospital leadership. The task force's predictive COVID-19 census output was specifically cited by hospital leadership as a key piece of evidence which directly influenced their pre-emptive decision processes for changing visitation policies, planning for elective surgery reductions, projecting ICU, emergency department, and respiratory therapy staffing needs, coordinating staffing for expansion of testing and hospital bed capacities, and projecting the number of patients that could be enrolled in clinical trials.

The task force's consistency also allowed a steady-state transition in its workload in several ways. First, the data governors were able to pass forward the operational management of the task force to administrative and clinical leadership of the Kern Center. Likewise, with key metric dashboards formatted and automated to update daily, task force members were able to converse more frequently over e-mail during plateau/low-spread months and reduce meeting frequency to "as necessary" when red-yellow-green alert status changed meaningfully in any of our hospital regions. As localized COVID-19 spikes occurred, such as those at our Arizona and Florida hospitals in July and our Midwest hospitals in November, the task force was able to rely on our surveillance dashboards and predictive modeling framework to identify increasing alert status and ramp-up meeting frequency and modeling updates until hospital COVID-19 census returned to a lower, non-alert status. The task force has documented its experience in a general framework (Table 2) and now maintains a baseline steady-state of sentinel COVID-19 activity with minimum effort needed on an ongoing basis for model or metric development, but with the ability to rapidly and effectively re-engage with the practice using our standardized modeling and communication toolset as new COVID-19 peaks occur.

CONCLUSION

During the weeks before the COVID-19 pandemic in the United States, our institution rapidly developed an interdisciplinary

TABLE 2. Framework for the Formation of a Coronavirus Disease 2019 Predictive Analytic Task Force to Inform Hospital Operations[a]

1. Create a concise mission and actionable deliverable(s) for a task force to accomplish.
Example: Predict ICU COVID-19 census in 1, 2, and/or 4 weeks.
2. Recruit task force members from a diverse set of subject-matter experts, pulling from operational/administrative, academic, and analytic resources, with representation of clinical leaders who can rapidly disseminate key findings to the practice.
3. Undertake rigorous and rapid assessment of available tools to determine applicability of potential external solutions.
4. Identify and aggregate key data sources — both internal and external.
5. Uses the EHR and lab data as close to real-time as possible.
6. Maintain flexibility to adjust based on what you learn from the data, and create internal solutions and alert thresholds as necessary.
7. Foster open communication and teamwork to encourage the growth and identification of related projects.
8. Summarize key messages and findings in a concise, scheduled, and consistent manner.

[a]COVID-19, coronavirus disease 2019; EHR, electronic health record; ICU, intensive care unit.

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predictive analytics task force to provide COVID-19 hospital census forecasting to help clinical leaders understand the potential short- and long-term impacts of the pandemic on hospital operations. Throughout the continually evolving pandemic, our task force has provided frequent and consistent summary messaging and insights that have helped the practice to anticipate and react to changing operational needs and opportunities, thus protecting our ability to care for all patients. Practice leadership has relied on the task force's predictive output as an important data-driven tool in their arsenal for hospital census and quality management. We believe the framework shared here for the deployment of a COVID-19 predictive analytics task force could be adapted for effective implementation at other institutions to provide evidence-based messaging for operational decision-making. For hospitals without such a structure, immediate consideration may be warranted with COVID-19 models warning of a sustained third-wave through the winter of 2020–2021.

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Abbreviations and Acronyms: **CDT** = case doubling time; **COVID-19** = coronavirus disease 2019; **DMC** = destination medical center; **EHR** = electronic health record; **ICU** = intensive care unit; **PPE** = personal protective equipment

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