

hospital mortality. Over one-third of inpatients required post-hospital healthcare services. Such info may help healthcare providers better allocate resources to take care of COVID-19 patients during the pandemic.

### IN2 CHARACTERISTICS OF PATIENTS DIAGNOSED WITH CORONAVIRUS DISEASE 2019 (COVID-19) ACROSS THE THREE WAVES IN THE US: A CLAIMS-BASED STUDY USING A LARGE NATIONAL SAMPLE



Divino V

*IQVIA, Falls Church, VA, USA*

**Objectives:** To assess how characteristics of patients diagnosed with COVID-19 have changed over the three waves in the US (April, July and November 2020) and evaluate the temporal relationship of disease severity. **Methods:** This retrospective database study used IQVIA's medical (Dx) and longitudinal prescription claims (LRx) databases. Patients with a new medical claim with a diagnosis code of COVID-19 (ICD-10-CM: U07.1) in April, July or November 2020 were identified (first diagnosis = index date). Demographics, comorbidities and prescriptions within 6-months pre-index and diagnoses (symptoms/complications) and healthcare resource utilization within 14-days pre- or post-index were descriptively assessed by index month. Logistic regression was used to evaluate adjusted odds of serious complication and hospitalization by index month. **Results:** The study sample comprised 1,401,309 patients diagnosed with COVID-19 (330,110 April/452,663 July/618,546 November). Half of April/July/November cohorts were female (53.5/56.0/53.7%) with mean age 57.4/47.3/50.1 years and mean CCI score 1.3/0.7/0.6. Region varied with 20.8/60.2/40.4% located in the South. The top 3 comorbidities were more common in April: hypertension (35.8/23.4/19.6%), T2DM (20.7/13.6/10.6%) and dyslipidemia (19.3/13.6/11.0%). Similarly, the top 3 symptoms were more common in April: cough (25.4/14.8/14.5%), fever (22.7/11.4/8.5%) and shortness of breath (19.8/11.3/9.9%). Pneumonia was the most common serious complication and highest in April (33.4/17.8/16.9%). Proportion with ER visit (42.1/36.1/32.4%) and hospitalization (32.5/17.3/14.7%) was highest in April; conversely, COVID-19 diagnostic testing (24.2/45.0/43.5%) was lowest in April. After adjusting for baseline characteristics, July/November cohorts were associated with 51.4/57.4% lower odds of pneumonia and 49.0/62.1% lower odds of hospitalization compared to the April cohort, respectively (all  $p < 0.0001$ ). **Conclusions:** This research confirms that the underlying population contracting COVID-19 has changed over time. While new cases have increased, the burden and severity of illness appeared to be highest in April. These changing trends likely reflect improvements in the knowledge, treatment and management of the disease, as well as increased testing.

### IN3 ECONOMIC VALUE AND HEALTH SYSTEM IMPACT OF REMDESIVIR IN TREATING HOSPITALIZED COVID-19 PATIENTS IN THE UNITED STATES



Sun F,<sup>1</sup> Jeyakumar S,<sup>2</sup> Smith N<sup>2</sup>

*<sup>1</sup>Gilead Sciences Inc., Foster City, CA, USA, <sup>2</sup>Maple Health Group, LLC, New York, NY, USA*

**Objectives:** In the ACTT-1 study in hospitalized adults with laboratory confirmed COVID-19, remdesivir was found to be superior to placebo in shortening time to recovery from COVID-19. However, the economic value and health system impact of remdesivir treatment is still unclear. This study evaluated remdesivir's long-term cost-effectiveness and impact on health system capacities versus standard of care (SoC) for hospitalized COVID-19 patients in the United States (US). **Methods:** A hybrid decision-tree and Markov model simulated health and economic outcomes for hospitalized adult COVID-19 patients (average age of 58.9 years) from a US health system perspective over a lifetime horizon. Clinical inputs (e.g., hospitalization duration, mortality) were extracted from the ACTT-1 trial and real-world data. Cost inputs were sourced from an internal analysis or from the literature. Remdesivir acquisition cost was \$390/vial, and patients were assumed to receive 6.25 vials per treatment course. One-way and probabilistic sensitivity analyses were performed. A separate treatment capacity analysis was performed on a national scale, assuming a population of 328,200,000 and one monthly incident cohort of 201,000 patients eligible for treatment. **Results:** Relative to SoC, remdesivir was associated with a decrease in total costs (savings of \$8,844.49 per patient), increased life years (+0.62), and quality-adjusted life years (+0.47). Remdesivir was therefore dominant versus SoC (less costly and more effective). Results were robust in one-way and probabilistic sensitivity analyses. In the treatment capacity analysis, remdesivir increased the available hospital capacity by 1.4%, available ICU capacity by 32.1%, and total ventilator capacity by 2.3%. **Conclusions:** Remdesivir is a cost-effective option for the treatment of patients hospitalized with mild, moderate, and severe COVID-19 versus SoC. In addition, due to its demonstrated ability to shorten time to recovery, remdesivir is projected to increase

treatment capacity by increasing the percentage of available hospital bed-, ICU bed-, and total ventilator capacity.

### IN4 NON-HEALTH CONSIDERATIONS IN ECONOMIC EVALUATIONS OF COVID-19 INTERVENTIONS: A SYSTEMIC REVIEW



Podolsky M, Kim D, Neumann PJ

*Tufts Medical Center, Boston, MA, USA*

**Objectives:** To examine whether and how economic evaluations for COVID-19 interventions incorporate non-health impacts. **Methods:** Using pre-specified keywords, we searched the National Institute of Health's iSearch COVID-19 portfolio, containing both pre-prints and peer-reviewed articles, as our primary database to identify economic evaluations of COVID-19 interventions in December 2020. We retained studies that empirically evaluated economic as well as health consequences of COVID-19 interventions. We supplemented our search with additional sources, such as Google Scholar, COVID Scholar, EconLit, and NBER. Based on the Second Panel's "Impact Inventory," modified for COVID-19, we examined in the identified studies any consideration of non-health impacts, such as reduced productivity due to remote work, short-term job-related income loss, long-term unemployment, and other impacts on gross domestic product (GDP), and other sectors (e.g., related to environment or housing). **Results:** Of 274 articles screened, 61 met our inclusion criteria. The sample was comprised of 39 (64%) cost-effectiveness analyses (CEA), 17 (28%) cost-benefit analyses, and 5 (8%) other economic evaluations. The most commonly examined intervention was mobility restrictions, including stay-at-home orders and travel/gathering bans (n=25, 41%), followed by testing strategies (n=15, 25%) and therapeutics (n=15, 25%). Out of 22 CEAs that reported cost-per-quality-adjusted-life-years (QALY) outcomes, the median incremental cost-effectiveness ratio was lowest for therapeutics (\$848/QALY, n=7, inter-quartile range [IQR]: \$547-\$10,306) and highest for testing strategies (\$2,172,300/QALY, n=9, IQR: \$993,550-31,376,150). Twenty-nine studies (47%) included some type of non-health impact, most commonly lost income (n=17, 28%), followed by GDP impacts (n=11, 18%) and productivity (n=6, 10%). **Conclusions:** Consideration of non-health impacts is lacking in evaluations of COVID-19 interventions. Omission of these impacts can skew the value of pharmaceutical and non-pharmaceutical interventions and could have consequences for policy determinations as the pandemic continues. Researchers should consider including societal impacts in their analyses to more closely reflect the true value of interventions.

## Machine Learning Applications in Health

### ML1 COMPARING MORTALITY IN CARDIAC PATIENT SURGICAL CLUSTERS WITH MACHINE LEARNING CLUSTERS IN THE NATIONAL INPATIENT SAMPLE



Gala K,<sup>1</sup> Lodaya K,<sup>2</sup> Marinaro X,<sup>2</sup> Zhang X,<sup>2</sup> Hayashida DK,<sup>2</sup> Munson S,<sup>2</sup> D'Souza F<sup>2</sup>

*<sup>1</sup>Deborah Heart and Lung Center, Browns Mills, NJ, USA, <sup>2</sup>Boston Strategic Partners, Inc., Boston, MA, USA*

**Objectives:** This study investigates mortality in cardiac patient clusters based on surgery type versus patient clusters created through unsupervised machine learning (ML). **Methods:** The 2017 National Inpatient Sample describes US patient discharges and is provided by the Healthcare Cost and Utilization Project (HCUP). Patients included in this study were  $\geq 18$  years old with a "Major Therapeutic" primary cardiac procedure per HCUP Procedure Classes and Clinical Classification Software, and with a complete discharge record. Clusters were created through two different methods: 1) based on the three most common cardiac procedures; 2) based on patient and hospital characteristics, independent of mortality, through the ML algorithm K-prototypes. **Results:** A total of 170,326 discharges met inclusion criteria. The three prevalent cardiac procedures were percutaneous transluminal coronary angioplasty (PTCA) – 40.2%, coronary artery bypass graft (CABG) – 16.1%, and heart valve procedures (HV) – 15.0%. The prevalent procedures within each ML cluster were: Cluster 1: PTCA – 31.2% and CABG – 22.6%; 2: HV – 30.1% and CABG – 20.5%; 3: PTCA – 73.7% and CABG – 8.6%. The surgery clusters contained 121,423 discharges, while the ML clusters contained all 170,326 discharges. While the average Elixhauser Comorbidity Indices (ECI) based on the surgery clusters were different (PTCA: 2.1; CABG: 3.6; HV: 4.6;  $p < 0.0001$ ), the ML clusters revealed a clear difference in the average ECI (Cluster 1: 9.8; 2: 2.9; 3: 0.8;  $p < 0.0001$ ). While the mortality rate within each surgical group was different (PTCA: 1.6%; CABG: 1.7%; HV: 2.3%;  $p < 0.0001$ ), the ML clustering exposed a stark distinction in mortality between clusters (Cluster 1: 7.6%; 2: 0.8%; 3: 0.7%;  $p < 0.0001$ ).

**Conclusions:** A novel application of unsupervised ML in cardiac surgical patients identified a high mortality cluster otherwise missed by traditional classification. This high mortality cluster warrants further research to understand the typical patient journey and support treatments that may reduce the mortality rate.

### ML2 SUPERVISED MACHINE LEARNING PREDICTS MORTALITY IN COVID-19 PATIENTS USING ELECTRONIC HEALTH RECORDS

**Marinero X,** Meng Z, Zhang X, Lodaya K, Hayashida DK, Munson S, D'Souza F

*Boston Strategic Partners, Inc., Boston, MA, USA*

**Objectives:** This study implements supervised machine learning (ML) to predict mortality in COVID-19 patients and determine the important features in this prediction. **Methods:** Patients were selected from a large US electronic health records database (Cerner Real-World Data) that contains over 87 million patients. We investigated the first in-patient visit for patients with a COVID-19 diagnosis and lab results identified in the database, and with a length of stay of at least 24 hours, non-missing gender, and age between 18 and 90 years. Patient characteristics, hospital characteristics, Charlson Index, quick sequential organ failure assessment (qSOFA), treatments (e.g., mechanical ventilation) and lab values (e.g., minimum white blood cell count) were included in this analysis. Several ML algorithms were compared through 10-fold cross validation. The best performing algorithm was tuned and evaluated with a test dataset. Feature importance was extracted from the final model through permutation importance. **Results:** There were 55,045 patients included in this study. The ML algorithms that were compared included (mean cross-validation accuracy  $\pm$  cross-validation standard deviation): logistic regression (78.3%  $\pm$  0.4%); random forests (87.4%  $\pm$  0.5%); extreme gradient boosting (XGBoost) (88.1%  $\pm$  0.5%); and support vector machines (83.1%  $\pm$  0.4%). XGBoost was selected for the final model, which after hyperparameter tuning, had a prediction accuracy of 88.3%. The final model had an F1 score of 0.57, an area under the receiver operator characteristic curve (AUC ROC) of 0.90, a precision of 0.65, and a recall of 0.50. The top five most important features in this prediction were mechanical ventilation, age, minimum white blood cell count, qSOFA, and maximum temperature. **Conclusions:** Supervised ML was able to perform well in predicting mortality in COVID-19 patients, while identifying the most important features in prediction. Similar ML algorithms may identify higher risk COVID-19 patients earlier in the hospital for additional monitoring and treatment consideration.



### ML3 LASSO (LEAST ABSOLUTE SHRINKAGE AND SELECTION OPERATOR) AND XGBOOST (EXTREME GRADIENT BOOSTING) MODELS FOR PREDICTING DEPRESSION-RELATED WORK IMPAIRMENT IN US WORKING ADULTS

**Li V,** Costantino H,<sup>1</sup> Rowland J,<sup>2</sup> Yue L,<sup>3</sup> Gupta S<sup>1</sup>

<sup>1</sup>Kantar, New York, NY, USA, <sup>2</sup>Kantar, Bronx, NY, USA, <sup>3</sup>Kantar, Jersey City, NJ, USA

**Objectives:** Work productivity loss among adults with depression are associated with multiple patient characteristics. The current study examined predicted total work impairments as a result of absenteeism and presenteeism using regularized linear regression and decision-tree-based ensemble algorithm. **Methods:** Data on employed US adults (18–64 years old) were analyzed from the 2019 National Health and Wellness Survey. Analysis sample included respondents who self-reported diagnosis of depression or having experienced depression in the past 12 months. Work productivity loss was derived from Work Productivity and Activity Impairment questionnaire. Group LASSO with Nesterov's method and XGBoost regression were used separately to predict work impairments and to extract model feature importance views. Given the count-like nature of productivity loss, poisson distribution was specified in both LASSO and XGBoost. Variable selection was based on model fit statistics Akaike Information Criterion (AIC) (LASSO) and the gain in feature importance (XGBoost). Forty variables on respondent demographics, health behavior (e.g., smoking and alcohol use), depression-related variables, comorbidities, and doctor visits were entered into both models. Data was split into training, validation, and testing datasets. Hyperparameters were tuned based on the validation data. Root mean squared errors (RMSE) for the testing data were compared to assess model performance. **Results:** Among 11,478 working adults with depression, XGBoost made more accurate predictions compared with LASSO (RMSE=26.6 and 27.6, respectively). Overestimation of impairment was slightly greater in the LASSO model compared with that from XGBoost (mean impairment=33% and 30%, respectively). The LASSO model selected more demographic and health behavior variables than XGBoost which



ranked comorbidity variables (arthritis, sleep conditions, migraine, liver or renal diseases) as the most important features in predicting productivity loss. **Conclusions:** In a broadly representative US population of working adults with depression, XGBoost model was found to better predict productivity loss compared with LASSO.

### ML4 ASSOCIATION OF INCIDENT CANCER WITH LOW-VALUE CARE AMONG ELDERLY MEDICARE BENEFICIARIES USING MACHINE LEARNING

**Iloabuchi C,**<sup>1</sup> Dwibedi N,<sup>2</sup> LeMasters T,<sup>2</sup> Ladani A,<sup>3</sup> Shen C,<sup>4</sup> Sambamoorthi U<sup>4</sup>

<sup>1</sup>West Virginia University School of Pharmacy, Robert C. Byrd Health Sciences Center, WV, USA, <sup>2</sup>West Virginia University School of Pharmacy, Morgantown, WV, USA, <sup>3</sup>West Virginia University Medicine, Morgantown, WV, USA, <sup>4</sup>Penn State College of Medicine, Hershey, PA, USA

**Objectives:** In the United States (US), 25% of healthcare spending is considered wasteful because it is spent reimbursing low-value care. Low-value care is the utilization of healthcare services, medical tests, and procedures that have unclear or no clinical benefit to patients, but still exposes them to risk. This study aims to evaluate the association of incident breast, prostate, colorectal and Non-Hodgkin's cancer to low-value non-cancer care among older US adults enrolled in Medicare using machine learning methods. **Methods:** We used a retrospective cohort study design with 12-month baseline and follow-up periods. We identified two cohorts of cancer and non-cancer patients. We identified relevant low-value services using ICD9/ICD10 and CPT/HCPCS codes. XGboost models were used to identify the leading predictors of low-value care and partial dependence plots to examine the association of the different cancer types to low-value care. **Results:** The combined study cohorts included 529,452 individuals. Overall, the prevalence of low-value care was 24.3%. Rates of low-value care differed significantly by cancer type; the highest rates were observed in Non-Hodgkin's lymphoma (34%) followed by colorectal cancer (29%) while the lowest rates were among patients diagnosed with prostate cancer (22%). The association of cancer to low-value care varied by cancer type; both colorectal cancer and NHL were positively associated with low-value care, but breast and prostate cancers were negatively associated with low-value care. **Conclusions:** One in four older fee-for-service Medicare beneficiaries received low-value care. The leading patient-level predictors of low-value care were fragmentation of care, the number of chronic conditions, and age. Community-level predictors like market characteristics, healthcare utilization, and social determinants of health were also found to be important predictors of low-value care, suggesting that a multipronged approach that targets patient and system-level factors are needed to reduce the risk of low-value care among older adults.



## Medical Technology Studies

### MT1 TELEHEALTH UTILIZATION AND MULTIPLE SCLEROSIS IMAGING UTILIZATION IN FOUR MS CENTERS DURING THE COVID PANDEMIC: REAL-WORLD EVIDENCE FROM THE MS-CQI IMPROVEMENT RESEARCH COLLABORATIVE.

**Chen A,**<sup>1</sup> Molaei M,<sup>2</sup> Vaeth A,<sup>3</sup> Walsh K,<sup>1</sup> Oliver B<sup>4</sup>

<sup>1</sup>Thomas Jefferson University, Philadelphia, PA, USA, <sup>2</sup>Thomas Jefferson University, Conshohocken, PA, USA, <sup>3</sup>Massachusetts General Hospital; Harvard Medical School, Charlestown, MA, USA, <sup>4</sup>Dartmouth-Hitchcock-Health, Lebanon, NH, USA

**Objectives:** To describe care utilization types and related imaging utilization outcomes during the COVID pandemic. **Methods:** Electronic Health Record (EHR) data from four participating MS-CQI centers was abstracted for January–June 2020. Participants were patients with Multiple Sclerosis (PwMS)  $\geq$  18 years who were seen either in person or via a telehealth method such as phone or video. Chi-square tests were used to assess associations across centers and different types of telehealth utilization variables. ANOVA was used for continuous variables. Associations between 3 types of magnetic resonance imaging (MRI) utilizations [brain MRI (bMRI), cervical MRI (cMRI), and thoracic MRI (tMRI)] and care delivery type (telehealth or in-person) were assessed using binary logistic regression. **Results:** The study included 1,866 PwMS with the majority being female (75%), having RRMS (81%), and an average age of 49 years. 1,014 patients used a telehealth method during the time period whereas 852 patients utilized in-person physician visits. Controlling for covariates, regression analyses identified significant center effects on MRI imaging usage during the pandemic. Telehealth utilizers had greater odds of using imaging services compared to in-person utilizers for brain MRI (bMRI), cervical MRI (cMRI),

