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Objectives
- Increase awareness of machine learning methodologies.
- Explain how machine learning augments human prognostication.

Importance. Significant mismatches exist between patient wishes and care delivery at the end of life. While global capture of end of life patient care preferences remains elusive for the healthcare system, another challenge, especially in an era of rapidly advancing therapies, is accurate prognostication.

Objective(s). Increase awareness of machine learning methodologies and use in prognostication.

Method(s). We developed a supervised machine learning model utilizing data from 2014-2017 on 18,797 cancer patient records with the goal of predicting 90-day mortality utilizing up to 180 days of data prior to the prediction date. Using a gradient boosted tree algorithm, evaluating 205 features (encompassing labs, age, gender, vitals, medications, and utilization), we trained the model on 14,431 patients and evaluated the model on 4,366 patients, of which 116 patients died within 90 days of the prediction date.

Leveraging gradient boosted tree allows limited insight into the predictions (i.e., a gray box model). Using the SHapley Additive exPlanations (SHAP) method, we were able to estimate the contribution of each feature on the prediction score of each true positive patient.

Results. Performance on the evaluation set showed a ROC AUC of 0.94 and an average precision (area under the precision-recall curve) of 0.44. We set a decision threshold for a precision of 70%. The model flagged 29 patients, 20 of which were true positives (17.2% recall). The highest weighted features predictive of 90-day mortality in this true positive population included known prognostic factors such as albumin, weight change, and performance status. Machine learning allows more sophisticated analysis, and the model found significance in unique aspects of the data (i.e., evaluating the slope of lab values, minimum value of albumin, or the maximum value for alkaline phosphatase). Other highly prognostic variables are intuitive, but beyond human capability to easily compute, including the percent of all normal labs.

Conclusion(s). Machine learning with explanation models to predict prognosis shows promise, but requires further evaluation.

A Machine Learning Based Risk Stratification Tool to Coordinate Referrals Between Inpatient Specialty and Palliative Care for Patients with Heart Failure (RP320)

Objectives
- Explain how clinical stakeholders were involved in the multidisciplinary model building process of our model.
- Explain what results of our risk score look like and how they can be used by cardiologists and palliative care teams to discuss and coordinate referrals.

Importance. Most inpatient palliative care teams rely on referrals from treating physicians. Reliable prognostication necessary to support timely referrals has proven challenging for treating physicians.

Objective(s). We engaged palliative care and cardiology providers to develop and evaluate a machine learning based risk stratification tool to identify patients with heart failure (HF) who are likely to die within 12 months of their hospitalization. Our tool will be shared with cardiology and palliative care teams and provides along with a risk score provider defined criteria such as frequent emergency department visits or high pain score to contextualize the risk score.

Method(s). We chose one randomly selected hospitalization for each patient (N=76,955) ages 18+ years with a diagnosis of HF who was hospitalized during 06-2007 to 10-2015 across 14 Kaiser Permanente Southern California (KPSC) hospitals. Predictive models were built and tested using extreme gradient boosting and cross-validation on 90% of the sample. Validation was conducted on the remaining 10%. Our predictor set is drawn from the highest performing models in the literature and clinician input.
Clinicians choose specific predictors to display along with the risk score.

**Results.** The model area under the curve (AUC) is 0.83, sensitivity is 66%, and the positive predictive value (PPV) is 79% for default probability cut-offs. PPV can be increased to 90% with a sensitivity of 41%, and changes in referral volume for different probability cut-offs will be presented across hospitals and all of KPSC. Models will be run nightly. We will work with clinicians to identify palliative and cardiology team members who should receive the risk score every morning and discuss referrals.

**Conclusion(s).** We engaged with key clinical stakeholders to design and validate a high-performing risk-stratification model to target and coordinate referrals between specialty and palliative care providers.

**Impact.** Our tool can facilitate and optimize specialty-palliative care-team discussions and palliative care referrals.

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**Living with Versus Dying from End Stage Renal Disease: Dialysis Patients’ Experiences with Advance Care Planning (RP321)**

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**Objectives**

- Discuss dialysis patients’ perspectives on provider communication about options for renal replacement therapy.
- Describe the barriers to advance care planning conversations in end stage renal disease.

**Importance.** People with end stage renal disease (ESRD) experience higher treatment intensity, more hospitalizations and lower rates of advance care planning near the end of life than people with other serious illnesses. Comprehensive care of people with ESRD includes advance care planning conversations that address goals of care well beyond choices between specific options for renal replacement therapy.

**Objective(s).** The objective of this study was to explore the nature of advance care planning and how provider communication influences a sense of coherence about illness and treatment in a sample of dialysis patients.

**Method(s).** In-depth chairside interviews involving the collection of both qualitative and quantitative data were conducted with 35 participants while they were on dialysis. Open-ended questions focused on the history of illness, development of understanding about the disease and its impact on their lives, goals of care, and what gives life meaning. Categorical questions focused on the timing and quality of provider communication about healthcare decisions using the QEOLC-10, if they had a healthcare proxy, and what the person knew about their wishes.

**Results.** Participants $M_{age} = 55.8 (SD = 17)$; 77% were African American, 20% White and 3% Latinx; 57% were female. The length of time on dialysis ranged from 4 months to 24 years. A majority (89%) had a healthcare proxy and 77% said the person would know their wishes if unable to speak for themselves. The length of time it took to fully comprehend the complexity of being a dialysis patient ranged from 6 months to 3 years. Four themes were illuminated from the analysis of the narrative data: Differential Illness Trajectories (unexpected kidney failure, long-term diabetes, hypertension, transplant failure); Meaning Making is Coping; Provider Communication; and Living with (not Dying on) Dialysis.

**Conclusion(s).** Comprehension of the realities of dialysis is complex and focuses on life-affirming choices.

**Impact.** The unique and distinct decisions and experiences of ESRD underscore the importance of disease-specific and person-centered advance care planning conversations.

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**“Connection”—The Integration of a Person-Centered Narrative Interventions into the Electronic Health Record: An Implementation Study (RP322)**

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**Objectives**

- Describe barriers and facilitators to implementation of the co-created patient narrative intervention included in the electronic health record (EHR).
- Assess the acceptability and usability of including patient narratives in the EHR.

**Introduction.** Incorporating patient narratives into the EHR is an opportunity to integrate patients’ values into their care and improve patient-clinician communication.

**Objective(s).** The study’s aims were to (1) identify barriers and facilitators influencing the implementation of the integration of patient narrative intervention into the patient’s EHR and (2) assess the