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ISPOR EUROPE 2021

Risk of Hospitalization and Emergency Room Visits Among Community Oncology Patients

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Objective

- Explainable machine learning model to predict patient risk of emergency room (ER) visit and unplanned hospitalization within 30 days following a community oncology practice visit

Purpose

- Reduce unplanned hospitalization or ER visits
- Reduce overall cost of healthcare
- Improve Oncology Care Model (OCM) ER visit score
- Provide insights in patient risk

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Patient Population & Demographics

Data was collected from US Oncology Network (USON) practices enrolled in the Oncology Care Model (OCM) program starting from July 1, 2016 to June 30, 2020 (Performance Periods 1-8)

Data Sources

- *iKnowMed* Electronic Health Records (EHR)
- OCM claims data

Inclusion/Exclusion Criteria

- Patients over the age of 65
- Patient with a cancer diagnosis
- Patients enrolled in the OCM program (on active cancer therapy)

Outcome

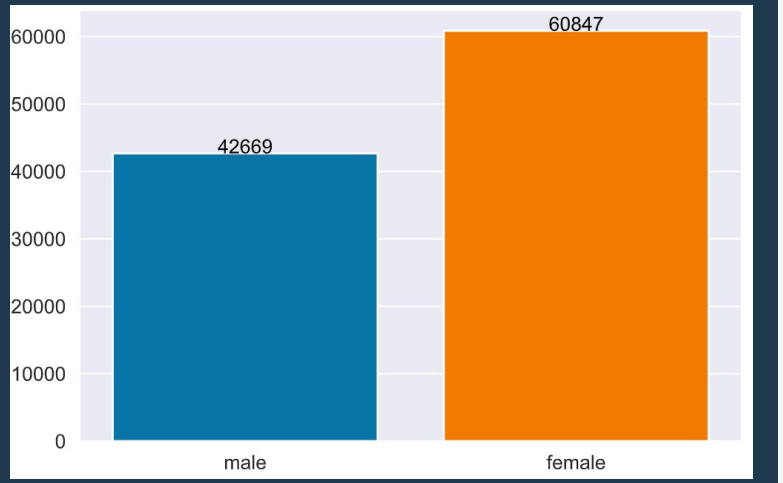
- Unplanned hospitalization/ER visit

Patient visit statistics

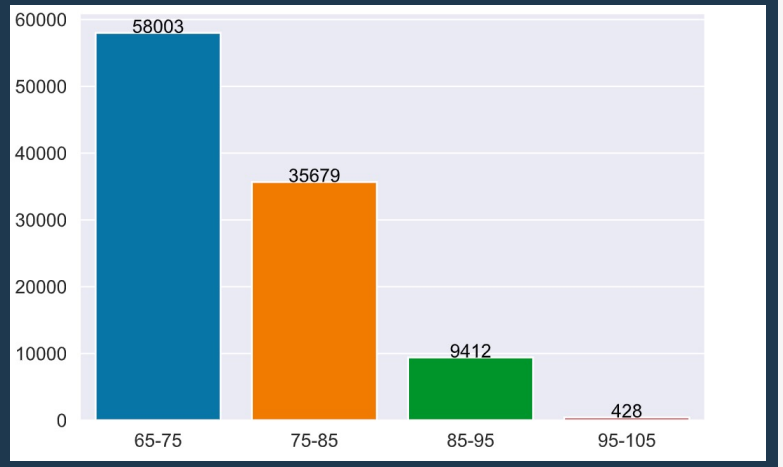
of Patients: 103,522

# of Visits: 3,537,967

Gender



Age



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Clinical Features

More than 300 features extracted

Labs	Duration of disease	ECOG Performance Status	Co-morbidities
Vitals	Pain	Weight loss percent	Cachexia
Demographics	Drugs	Treatment	Tumor Staging
Visit statistics	Metastatic disease	Cancer diagnosis	Derived features

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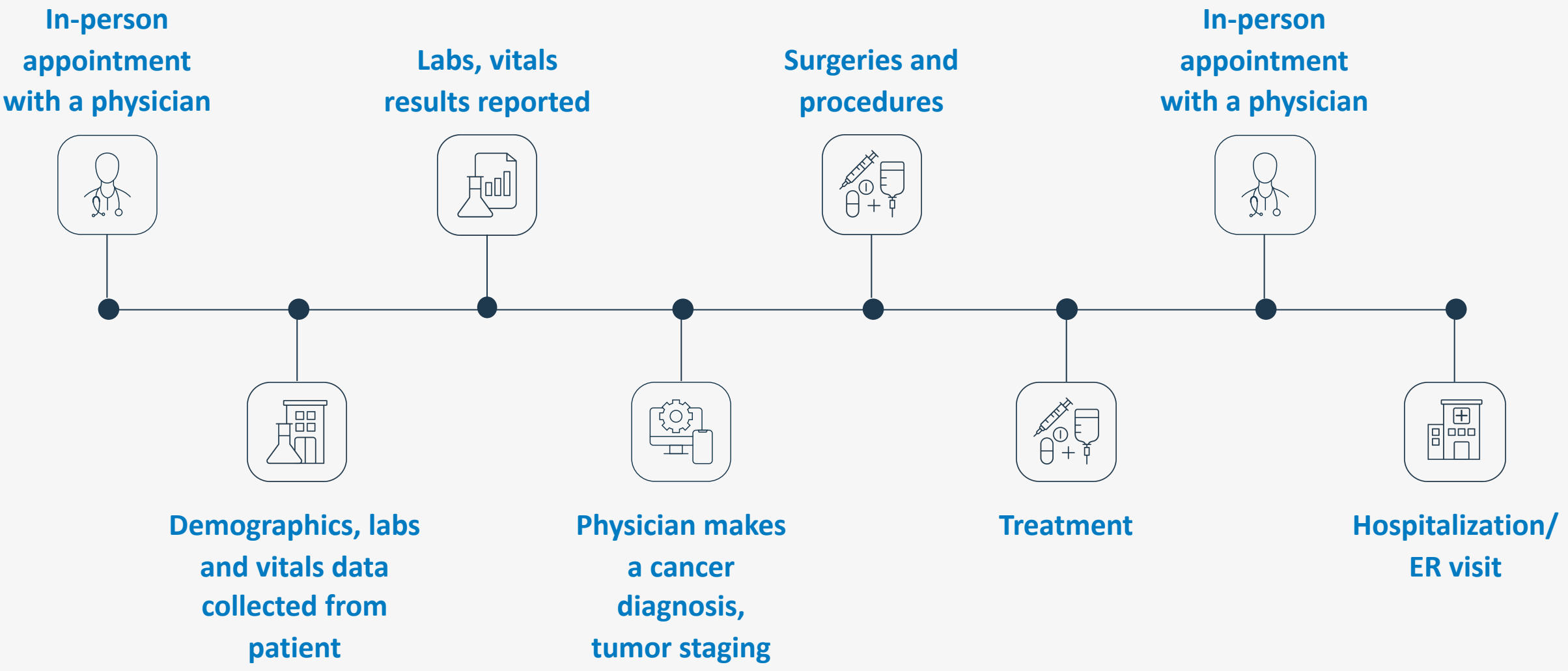
Methodology: Data collection



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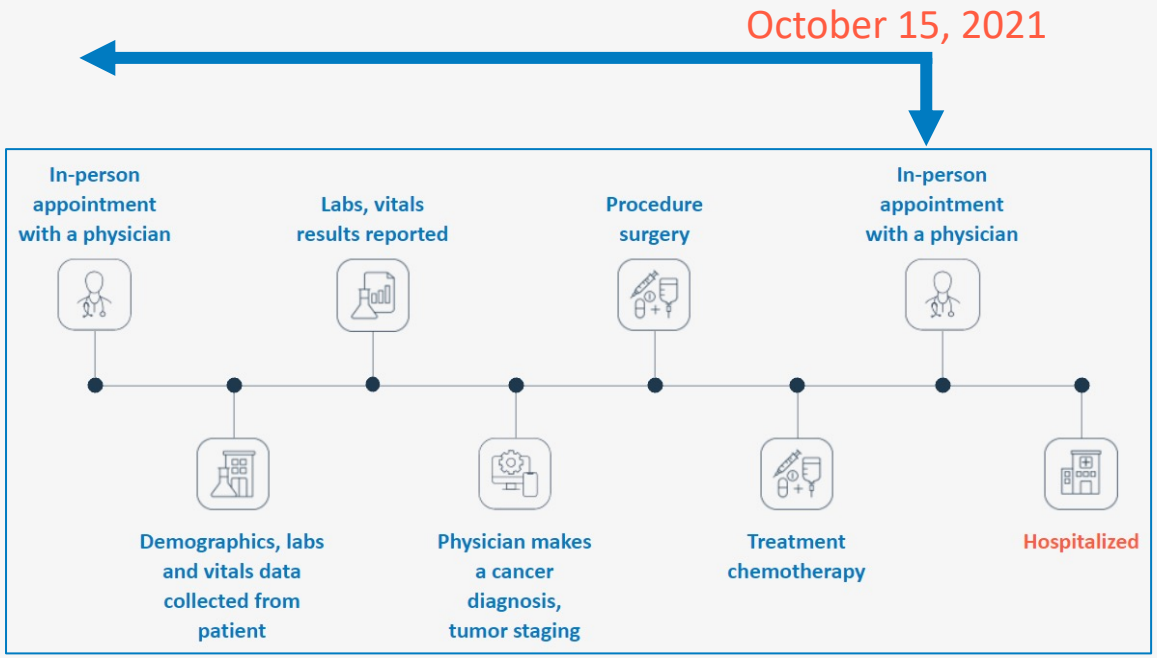
Methodology: Data transformation



Extraction of a record, with current and historical data, for a unique combination of patient and visit date

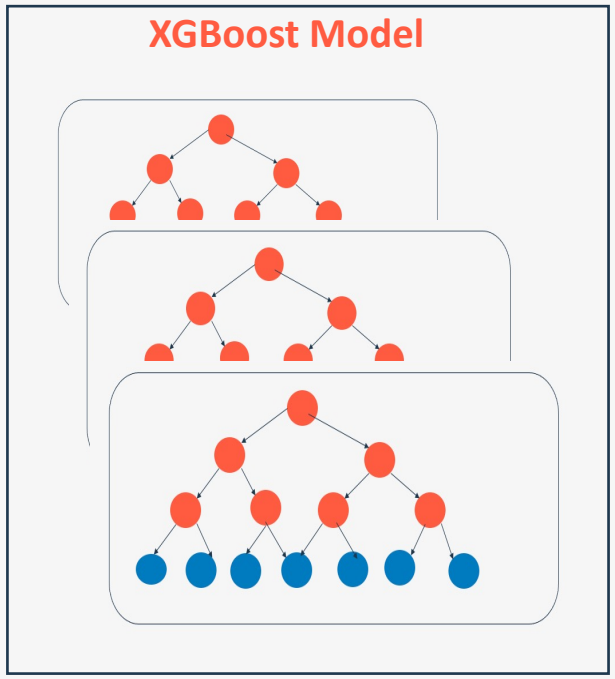
Patient ID	1234
Visit date	10/15/2021
Last Albumin in past 30 days	2.8
Last Hemoglobin in past 30 days	8.0
Weight loss percent	4%
Last Pulse in past 30 days	100
Metastatic	True (1)
…	…
Treatment in last 30 days	Chemotherapy
Hospitalization/ER visit in next 30 days	Yes

Methodology: Model Building, Evaluation & Explainability

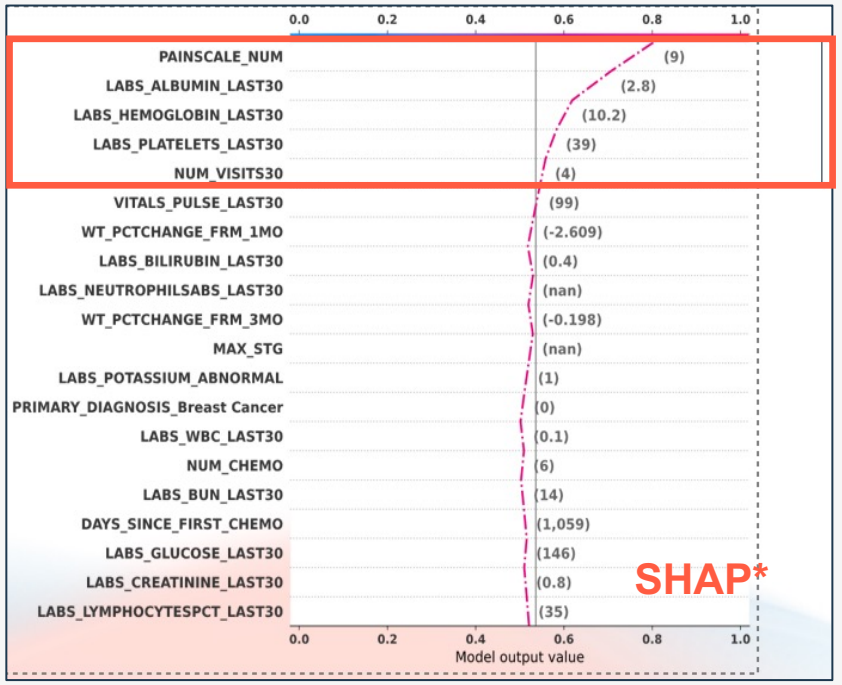
Patient Id	Visit Date	Lab: Albumin in last 30 days	Lab: Hemoglobin in last 30 days	…	Hospitalized/ ER visit
1023	9/01/2016				No
1134	10/20/2016	3.6	12.0		No
…	…	…	…		…
2342	9/19/2021	3	10		Yes
…					
1234	10/15	3.5	12..0		No

Training Set: 87%

Testing Set: 13%



Probability of hospitalization/ER visit: 0.8



Probability of hospitalization/ER visit	Risk Bucket	Distribution of patients (%)
0 – 0.59	Lowest risk	81.65%
0.60 - 0.69	Risk category 1	5%
0.70 - 0.79	Risk category 2	8.06%
0.80 - 0.89	Risk category 3	4.74%
≥ 0.90	Risk category 4	0.55%

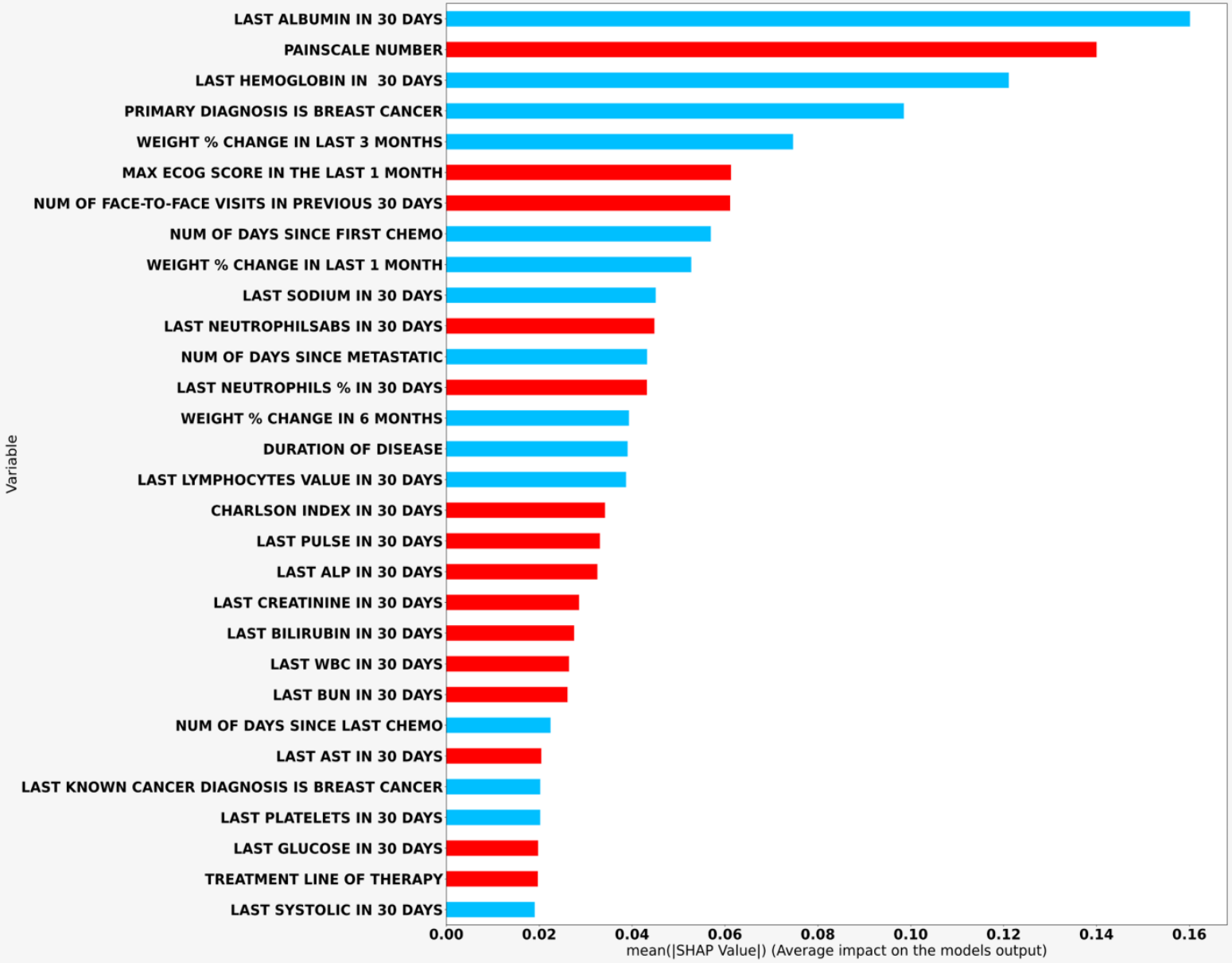
*SHapley Additive exPlanations

Results: Model Performance and Feature Ranking

Predicting 30 days in advance, no restrictions on cancer type/staging or treatment

Model	
Algorithm	XGBoost*
Area Under Curve (AUC)	72%
Sensitivity (Recall)	73% (Hospitalization/ER)
Specificity	60% (Non-Hospitalization/ER)
Threshold	50%

*eXtreme Gradient Boosting algorithm



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Limitations

- The model can only be applied to patients greater than 65 years of age
- OCM claims data is updated every 6 month, thus permitting retraining only every 6 months
- Unable to use previous hospital admissions or ER visits information during the model building phase as it would be an important factor in predicting future hospitalizations

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Conclusion

- Real-world data were harnessed and applied in an ML approach to establish a high-performing patient ER visit and hospitalization prediction model
- The next phase will include model deployment to several US Oncology Network practices to validate effectiveness in the real world
- Results will inform providers when a patient is at risk for an ER visit or hospitalization with the aim of improving the overall quality of oncology care and reducing admissions and ER visits

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Acknowledgement

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- Co-authors:

  Rahman MM, Mohammad N, Chang B, Karhade M, Robert N, Wu N, Heller B, Hoang S, Alwardt S, Neubauer M, Staggs S, Moore L, Smith H

- Data Science Team:

  Harrell R, Dwyer K, Kwon A, Crabtree M, Raju A

- Engineering Team:

  Crabtree C, Komara J

- Product Team:

  Ali R, McClendon E

- USON Team:

  Plagianis JD, Payne J, Ives H

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Thank You

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Backup slides

Definitions

- Weight loss percent:
  - Weight loss percentage of the current from the previous maximum weight in the last 1 month
- Cachexia:
  - No cachexia: weight change (± 1 kg) or weight gain
  - Pre-cachexia: weight loss ≥ 2%, but < 5%
  - Cachexia: weight loss > 5% the last 1 month, OR weight loss > 2% the last 1 month + BMI < 20 kg/m^2
  - Refractory cachexia: weight loss > 15% last 1 month + BMI < 23 kg/m^2 OR weight loss > 20% last 1 month + BMI < 27 kg/m^2
- Derived features:
  - Engineered features from labs and vitals (e.g. the maximum value of a lab minus the minimum value during a time period, abnormal lab/vital values)
- ECOG
  - Measures the daily ability of the patient to care for themselves.

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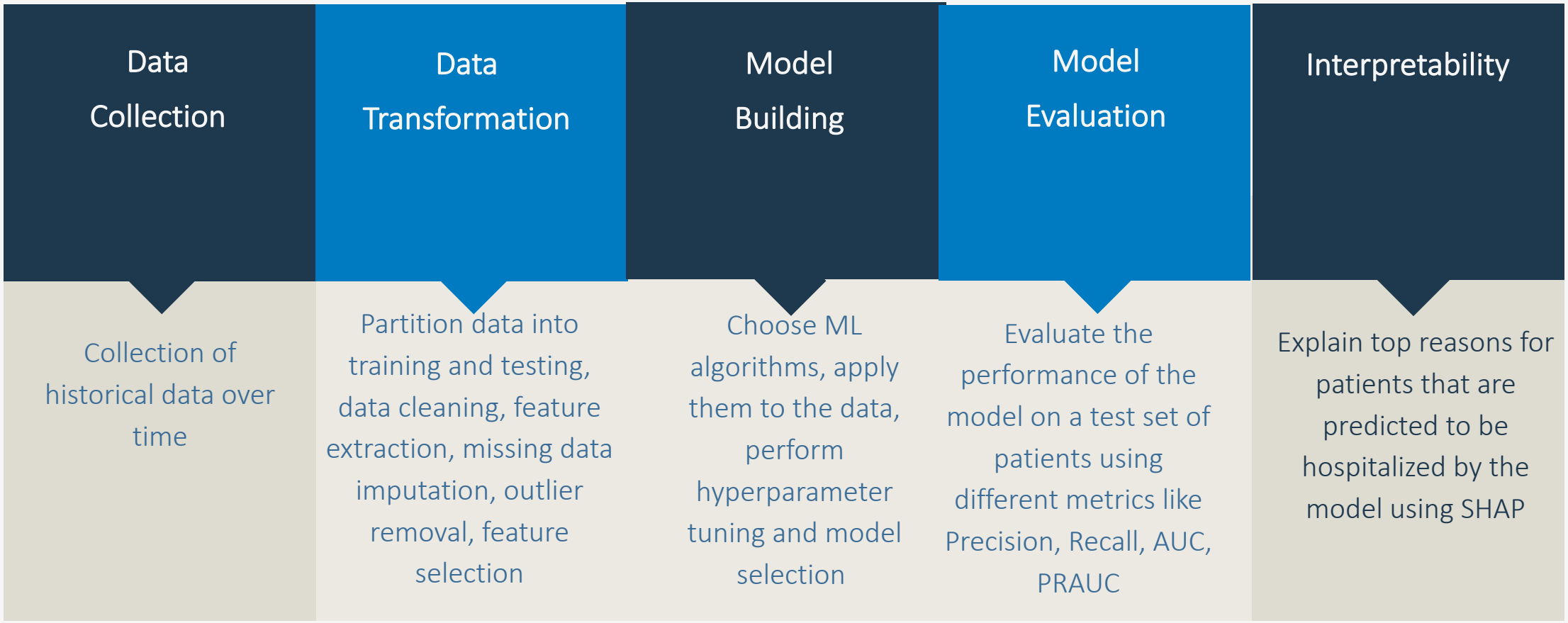
Methodology: Building an explainable predictive model for unplanned hospitalization



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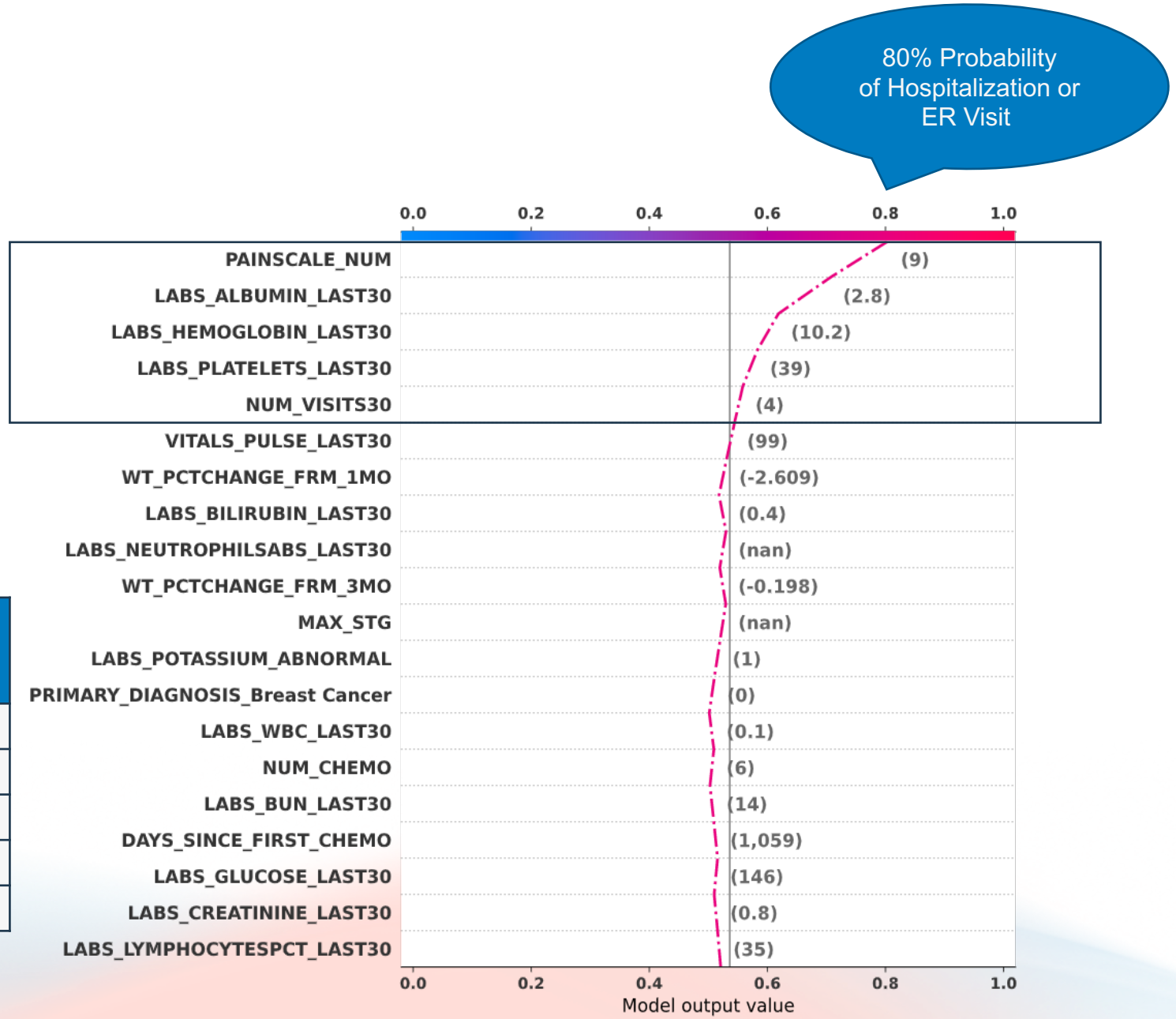
Explainability

- Explainability of Model:
  - Library: SHAP (SHapley Additive exPlanations)
  - Explanation: Top attributes for each individual hospitalization prediction

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