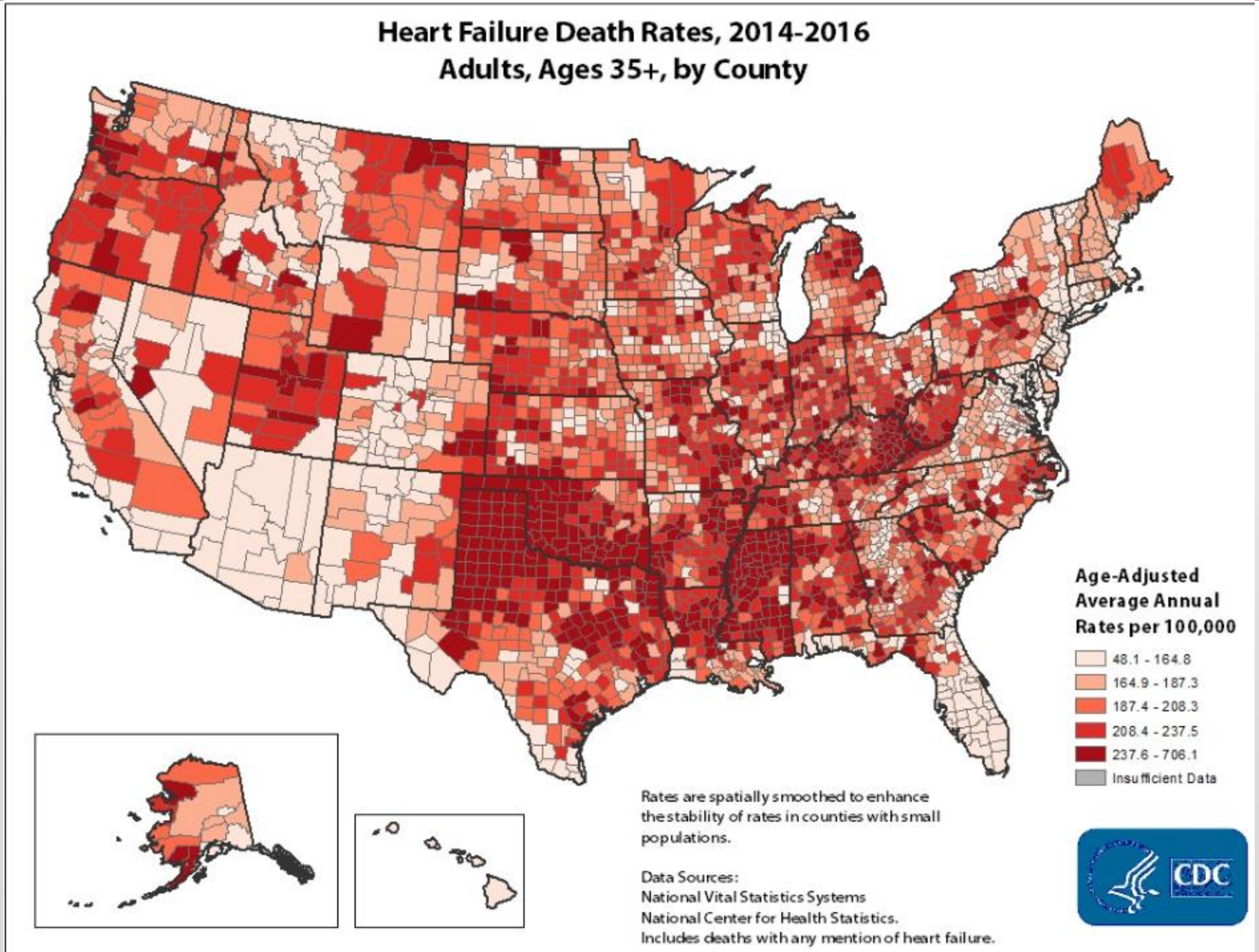
# Predict the effects of comorbidities on medication adherence among the heart failure patients

TORAL SHAH

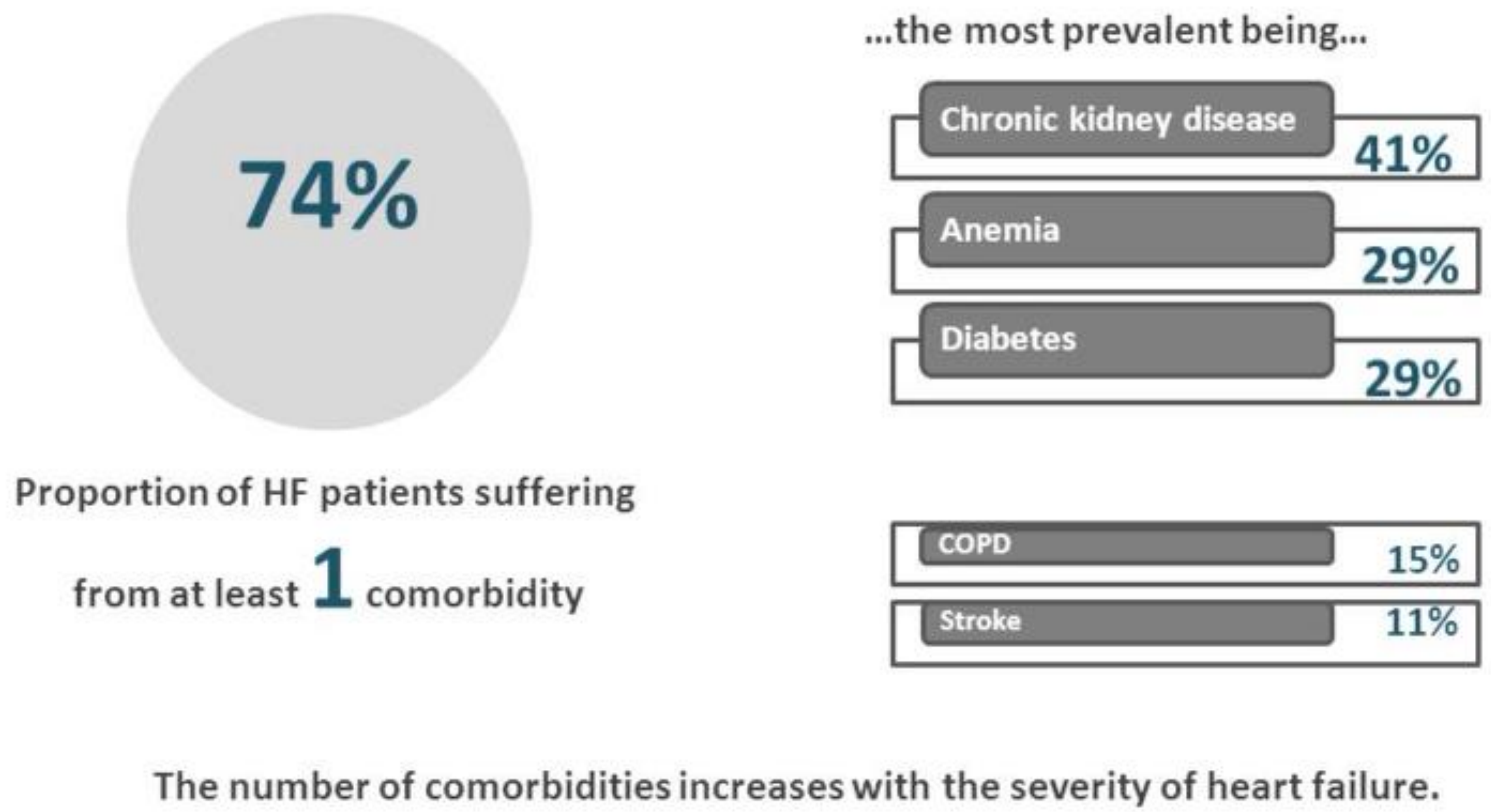
MENTOR: DR SAUL BLECKER

# Background

- According to CDC –About 6.2 million Americans suffer from Heart Failure in United States.
- Costing 380,000 lives and $30 billion dollar every year.
- Medication Adherence can reduce the number of deaths and ER admissions reducing the huge cost burden.



# Prevalence of comorbidities in heart failure




European HF pilot survey of 2014

Analyzed:

- 3226 HF patients
- Found comorbidities leading to increased morbidity, mortality and decreased quality of life

# Problem

- Comorbidity increases the number of medications.
- Complex medication regimen difficult to adhere.
- Medication Adherence Interventions have shown to reduce mortality and hospital readmission rate and healthcare cost.
- Recognizing the association of Comorbidities among HF patients and medication adherence will allow for an improved and standardized interventions.
- Machine Learning is  increasingly popular method of creating models of interventions yet there is lack of research and applications currently.

# Specific Aims

## Specific Aim # 1

- Develop a Machine Learning algorithms to predict effect (or association) of comorbidities (such as DM, hypertension, obesity) on Medication Adherence in patients who are diagnosed with heart failure at the time of hospital discharge based on EHR clinical data with geographical area in New York city.

## Specific Aim # 2

- Assess the differences of the effects of comorbidities on Medication Adherence among the patient subgroups based on social and economic factors.

# Methods

- **Data Collection**

Build a patient cohort 1 and perform data pull # 1

Age>=18, dx =icd code i50* (heart failure), discharge dates between September 1,2020 to June 30,2021

Build a patient cohort 2 and perform data pull # 2

From the patient id cohort # 1 – pull medication orders, medication dispensed

Build a patient cohort 3 and perform data pull # 3

From the patient id cohort # 1 – pull comorbidity data based on Charlson Index and Elixhauser Index

# Methods

- **Data Processing - Medications**

Based on the data pull # 2 & Clinical Team advise

Finalize the Heart Failure medications list – Total 687 Medications pulled out from patient's order list-

Finalized number of medications – 528 Eligible Heart Failure medications list

Identified five classes of medications : ACEI/ARB, ARNI, BB, MRA, SGLT2i

Mapped all medications to above identified classes names

# Methods

- **Data Processing – Medications – Calculate Proportion of Days Covered (PDC)**

PDC: Proportion of Days Covered: ratio of the number of days the patient is covered by the medication to the number of days patient is eligible to have the medication on hand.

Defined Definitions for calculating Numerator and Denominator

**Denominator = Medication End Date – Medication Start Date**

**Numerator = sum of complete fills + partial fills + stockpiled fills**

**Complete fills – are those whose entire fills are within the timeframe of interest, so the entire fill is included.**

**Partial fills – are those where medication fills obtained at the end of the denominator period.**

**Stockpiled fills – are those where medications are available from before the start date.**

# Methods

- **Data Processing - Medications**

Defining rules for calculating multiple medication classes

- For patients on just one class of medication, calculate PDC for that one class.
- For patients who are prescribed on two or more classes, calculate PDC for all medications and then calculate mean PDC across medications of same class.
- Patient is considered non medication adherence if  calculate PDC score is <= 0.80%.
- Used R programming language and created function to calculate PDC score.

# Methods

- Data Processing – Comorbidities Elixhauser Index

| Comorbidities | |
|---|---|
| Congestive heart failure | 398.91, 402.01, 402.11, 402.91, 404.01, 404.03, 404.11, 404.13, 404.91, 404.93, 425.4-425.9, 428.x |
| Cardiac arrhythmias | 426.0, 426.13, 426.7, 426.9, 426.10, 426.12, 427.0-427.4, 427.6-427.9, 785.0, 996.01, 996.04, V45.0, V53.3 |
| Valvular disease | 093.2, 394.x-397.x, 424.x, 746.3-746.6, V42.2, V43.3 |
| Pulmonary circulation Disorders | 415.0, 415.1, 416.x, 417.0, 417.8, 417.9 |
| Peripheral vascular disorders | 093.0, 437.3, 440.x, 441.x, 443.1-443.9, 447.1, 557.1 557.9, V43.4 |
| Hypertension, uncomplicated | 401.x |
| Hypertension, complicated | 402.x-405.x |
| Paralysis | 334.1, 342.x, 343.x, 344.0-344.6, 344.9 |
| Other neurological disorders | 331.9, 332.0, 332.1, 333.4, 333.5, 333.92, 334.x-335.x, 336.2, 340.x, 341.x, 345.x, 348.1, 348.3, 780.3, 784.3 |
| Chronic pulmonary disease | 416.8, 416.9, 490.x-505.x, 506.4, 508.1, 508.8 |
| Diabetes, uncomplicated | 250.0-250.3 |
| Diabetes, complicated | 250.4-250.9 |
| Hypothyroidism | 240.9, 243.x, 244.x, 246.1, 246.8 |
| Renal failure | 403.01, 403.11, 403.91, 404.02, 404.03, 404.12, 404.13, 404.92, 404.93, 585.x, 586.x, 588.0, V42.0, V45.1, V56.x |
| Liver disease | 070.22, 070.23, 070.32, 070.33, 070.44, 070.54, 070.6, 070.9, 456.0-456.2, 570.x, 571.x, 572.2-572.8, 573.3, 573.4, 573.8,573.9, V42.7 |

# Methods

- Data Processing – Comorbidities Charlson Index

| Comorbidities | ICD-10 * |
|---|---|
| Myocardial infarction | I21.x, I22.x, I25.2 |
| Congestive heart failure | I09.9,I11.0, I13.0, I13.2, I25.5, I42.0, I42.5-I42.9, I43.x, I50.x, P29.0 |
| Peripheral vascular disease | I70.x, I71.x, I73.1, I73.8, I73.9, I77.1, I79.0, I79.2, K55.1, K55.8, K55.9, Z95.8, Z95.9 |
| Cerebrovascular disease | G45.x, G46.x, H34.0, I60.x-I69.x |
| Dementia | F00.x-F03.x, F05.1, G30.x, G31.1 |
| Chronic pulmonary disease | I27.8, I27.9, J40.x-J47.x, J60.x-J67.x, J68.4, J70.1, J70.3 |
| Rheumatic disease | M05.x, M06.x, M31.5, M32.x-M34.x, M35.1, M35.3, M36.0 |
| Peptic ulcer disease | K25.x-K28.x |
| Mild liver disease | B18.x, K70.0-K70.3, K70.9, K71.3-K71.5, K71.7, K73.x, K74.x, K76.0, K76.2-K76.4, K76.8, K76.9, Z94.4 |
| Diabetes without chronic complication | E10.0, E10.1, E10.6, E10.8, E10.9, E11.0, E11.1, E11.6, E11.8, E11.9, E12.0, E12.1, E12.6, E12.8, E12.9, E13.0, E13.1, E13.6, E13.8, E13.9, E14.0, E14.1, E14.6, E14.8, E14.9 |
| Diabetes with chronic complication | E10.2-E10.5, E10.7, E11.2-E11.5, E11.7, E12.2-E12.5, E12.7, E13.2-E13.5, E13.7, E14.2-E14.5, E14.7 |
| Hemiplegia or paraplegia | G04.1, G11.4, G80.1, G80.2, G81.x, G82.x, G83.0-G83.4, G83.9 |
| Renal disease | I12.0, I13.1, N03.2-N03.7, N05.2-N05.7, N18.x, N19.x, N25.0, Z49.0-Z49.2, Z94.0, Z99.2 |
| Any malignancy, including lymphoma and leukemia, except malignant neoplasm of skin | C00.x-C26.x, C30.x-C34.x, C37.x-C41.x, C43.x, C45.x-C58.x, C60.x-C76.x, C81.x-C85.x, C88.x, C90.x-C97.x |
| Moderate or severe liver disease | I85.0, I85.9, I86.4, I98.2, K70.4, K71.1, K72.1, K72.9, K76.5, K76.6, K76.7 |
| Metastatic solid tumor | C77.x-C80.x |
| AIDS/HIV | B20.x-B22.x, B24.x |

# Methods

```
select
  patient.pat_id,
  case when HIV.count_of_dx > 0 then 1 else 0 end HIV,
  case when CANCER.count_of_dx > 0 then 1 else 0 end CANCER,
  case when PULM.count_of_dx > 0 then 1 else 0 end PULM,……..
…..
from clr_patients.patient
--1779016 : "AIDS/HIV",
left join (select PAT_ID, count(DX_ID) COUNT_OF_DX
from clr_diagnoses.PAT_ENC_DX
    left join clr_diagnoses.GROUPER_DX_RECORDS on PAT_ENC_DX.DX_ID = GROUPER_DX_RECORDS.CMPL_DX_RECS_ID
    where GROUPER_DX_RECORDS.GROUPER_ID = '1779016’
group by PAT_ID) HIV on HIV.PAT_ID = PATIENT.PAT_ID
```

| | pat_id | hiv | cancer | pulm | chf | dementia | dmwocomplication | metastatic |
|---|---|---|---|---|---|---|---|---|
| 1 | [redacted] | 0 | 1 | 1 | 1 | 1 | 1 | 0 |
| 2 | [redacted] | 0 | 1 | 1 | 1 | 1 | 0 | 0 |
| 3 | [redacted] | 0 | 1 | 0 | 1 | 1 | 0 | 0 |

# Data Analysis - Preliminary

## Cohort 1 HF patients

- Heart Failure dx codes – CMS quality reporting – I50*
- Hospital discharge date selection – to avoid the high COVID admission rates
- Total # of HF patients at discharge 2179
- Total # of HF patients with comorbidities at discharge 1890
- Total # of patients with only Heart Failure and no comorbidities – 289
- 86.79 % of HF patients have one or more comorbidities in my selected cohort

## Cohort 2  HF Meds

- Average Total # of HF meds per patient : 2
- Total # of patients with medications order : 1307
- Total # of patients with pdc < 0.80: 660

Non-compliant: 50 %

# Data Analysis – Preliminary

## Cohort 3  Comorbidities

Average Total # of comorbidities per patient

- Dementia - 2179
- Rheum - 78
- MildLiver - 146
- Modseverliver -  23
- Pulm – 549
- Chf – 2168
- Weight loss – 192
- Alcohol Abuse – 36
- Blood loss Anemia – 193
- Peptic Ulcer – 42
- Deficiency Anemia – 858
- Depression – 93
- Dm_with_chronic_complications- 601
- Dm_without_chronic_complications – 561
- Fluid_electrolytes – 793
- HIV – 12
- Hypothyroidism – 365
- Liver disease – 130
- Lymphoma – 56
- Metastatic_cancer – 52
- Obesity – 436
- Other_neurologic_disorders - 324
- Paralysis – 30
- Peripheral_vascular – 540
- Psychoses – 41
- Pulmonary_circulation_disorders – 89
- Renal failure – 549
- Solid tumor without metastases – 257
- Valvular disease - 824
- Coagulation Disorder -217
- Hypertension - 1442

# Next Steps

- Continue further Data Analysis – breakdown of data by race, ethnicity and age.
- Re-run medication orders and dispensed queries as preliminary analysis found missing orders from about 1200 patients.
- Re-run PDC calculations based on new data.
- Verify ICD- 10 Codes with GrouperIDs pulling Comorbidities data.
- Breakdown of medications analysis by heart failure medications and all other medications to understand if there is a correlation between number medications and non-adherence.
- Use Python and Logistic Regression Machine Learning Model to predict the effect of comorbidities on medication adherence.