A Pilot Characterization Study Assessing Health Equity in Mental Healthcare Delivery within the State of Georgia

November 2022

Jacob Zelko (PI), Malina Hy, Varshini Chinta, Emily Liau, Morgan Knowlton

November, 2022

Georgia Tech Research Institute

Background

- Mental health care varies across populations

  - Internal reasons:
    - Beliefs
    - Attitudes

  - External reasons:
    - Socioeconomic factors
    - Insurance status
    - Experiences with care providers

Project Goals

Characterize populations with mental health conditions, investigate prevalence of mental health care, and utilization of mental health resources in rural and urban US communities

- Target 1: Identify vulnerable populations and their characteristics
- Target 2: Enable large scale observational health research

Project Goals: Target 1

Identify vulnerable populations and their characteristics

- Leverage claims data, electronic health records, surveys
- Develop clinical phenotypes around mental health conditions
- Focus around depression, bipolar disorder, suicidality

Project Goals: Target 2

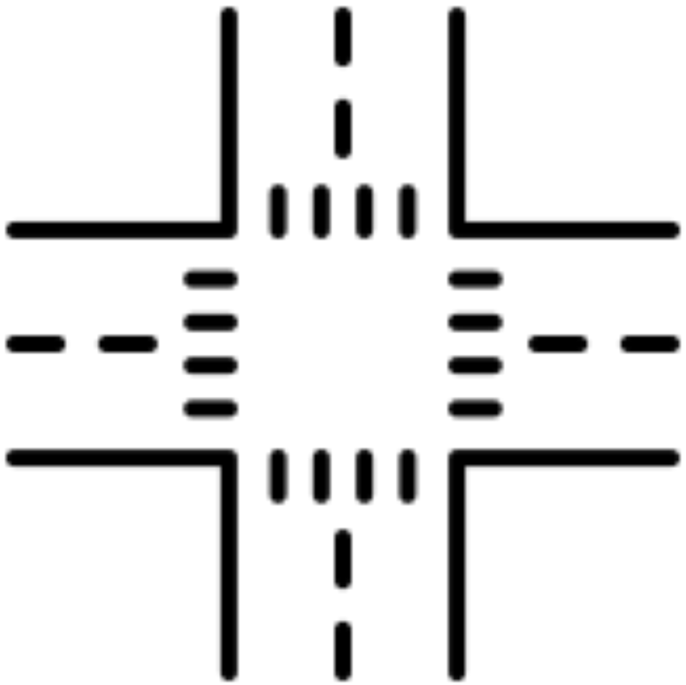
Enable Large Scale Observational Health Research

- Utilize a federated research model
- Align research package with OHDSI standards
- Develop strategic partnerships with data partners

What Is Meant by Characterization

Characterize individuals seen for mental health care at least once across axes such as:

- Condition
- Age
- Race
- Gender
- Location
- Care setting



Characterization Analyses

Baseline Characterization: Characterize the individuals being seen for mental health care services (related to depression, bipolar disorder, and suicidal ideation) at least one time – including hospitalization events.

Characterization Schemes

- **Follow-up Characterization:** Characterize patients who are seen only one time for mental health conditions. Areas of interest include:
  - How do the characteristics of patients who are seen only one time for mental health conditions differ from those who continue to receive care?
  - Of the patients who are seen only once for mental health conditions, do they continue to be seen for other conditions?
  - For those who continue to receive mental health care, how do outcomes for other conditions differ from those who were seen only once?

A Pilot Characterization Study Assessing Health Equity in Mental Healthcare Delivery within the State of Georgia

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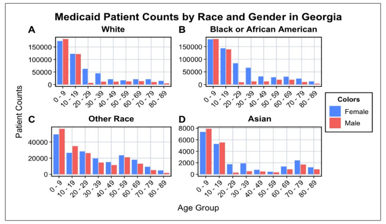
Background

Healthcare disparities continue to be a concern in the US. [1,2] Issues persist across population factors, such as race [3], socioeconomic status [3], provider availability [4], geographic location [5], and their intersections [7]. One region that is known for vulnerability factors [9] is the state of Georgia as it records the poorest mental health outcomes in the US [8] and is highly racially and ethnically diverse [10]. A pilot characterization was performed to establish baseline metrics to potentially assess differences in access to care and in diagnostic practices across bipolar disorder, depression, and suicidality patient subpopulations.

Methods

Data Source: ~2.2 million Georgia Medicaid claims from the Centers for Medicare and Medicaid Services (CMS) were studied over 1999 – 2014 via the Personal Summary, Inpatient, Other Services, and Prescription Drug MAX Files. The right figure shows the spread of these patients by gender and age groupings broken out across race.



Tools: Novel tooling (fig. & tab. left) was prototyped to define, examine, and explore niche subpopulations (fig. right) by strata (e.g. race, condition, age group, etc.).

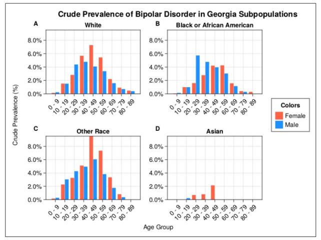
```
import DataFrames: Not, combine, groupby, nrow, outerjoin
import OMOPCDMCohortCreator as occ
import HealthSampleData: Eunomia
import SQLite: DB

conn = DB(Eunomia())
occ.GenerateDatabaseDetails(:sqlite, "main")
occ.GenerateTables(conn)

patient_ids = [6, 123, 129, 16, 65, 74, 38, 187, 18, 111]

patients_gender = occ.GetPatientGender(patient_ids, conn)
patients_age_groups = occ.GetPatientAgeGroup(patient_ids, conn)

patient_df = outerjoin(patients_gender, patients_age_groups; on = :person_id) |>
         df -> df[:, Not(:person_id)] |>
         df -> groupby(df, [:gender_concept_id, :age_group]) |>
         df -> combine(df, nrow => :counts
```

gender_concept_id	race_concept_id	age_group	counts
8532.0	8516.0	50 - 59	2
8507.0	8527.0	70 - 79	2
8507.0	8527.0	40 - 49	1
8532.0	8527.0	50 - 59	4
8532.0	8527.0	40 - 49	1

Outcome Measures: Crude prevalence rates for patient subpopulations were computed. The period, *p*, are the years data was examined, simplifying period prevalence, (1), to (2) where, *C*, are patients meeting a subpopulation criteria and, *N*, are all patients matching a subpopulation.

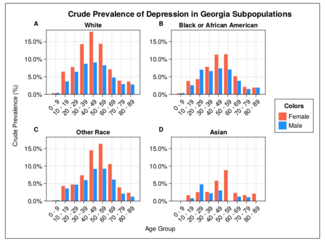
$$(1)\quad P = \frac{C + C_p}{N + N_p} \qquad\qquad (2)\quad P = \frac{C}{N}$$

Results



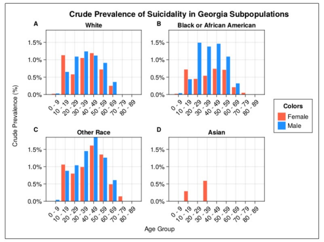
	White		Black or African American		Other Race		Asian	
Age Groups	Male Prev. (%)	Female Prev. (%)	Male Prev. (%)	Female Prev. (%)	Male Prev. (%)	Female Prev. (%)	Male Prev. (%)	Female Prev. (%)
0 - 9	0.24 (0.0)	0.14 (0.0)	0.14 (0.1)	0.06 (0.08)	0.27 (-0.03)	0.16 (-0.02)	N/A	N/A
10 - 19	1.51 (0.0)	1.53 (0.0)	0.99 (0.52)	0.99 (0.54)	3.04 (-1.53)	2.27 (-0.74)	0.22 (1.29)	N/A
20 - 29	4.38 (0.0)	2.82 (0.0)	5.73 (-1.35)	1.6 (1.22)	4.27 (0.11)	3.26 (-0.44)	N/A	0.69 (2.13)
30 - 39	4.78 (0.0)	5.68 (0.0)	4.77 (0.01)	2.78 (2.9)	4.95 (-0.17)	5.12 (0.56)	N/A	0.8 (4.88)
40 - 49	4.08 (0.0)	7.27 (0.0)	3.96 (0.12)	4.21 (3.06)	6.06 (-1.98)	9.53 (-2.26)	N/A	2.14 (5.13)
50 - 59	3.38 (0.0)	5.44 (0.0)	3.04 (0.34)	4.25 (1.19)	3.83 (-0.45)	7.35 (-1.91)	N/A	N/A
60 - 69	1.59 (0.0)	2.2 (0.0)	1.15 (0.44)	1.57 (0.63)	1.76 (-0.17)	3.35 (-1.15)	N/A	N/A
70 - 79	0.71 (0.0)	0.91 (0.0)	0.29 (0.42)	0.4 (0.51)	0.36 (0.35)	0.81 (0.1)	N/A	N/A
80 - 89	0.39 (0.0)	0.48 (0.0)	N/A	0.29 (0.19)	N/A	N/A	N/A	N/A

Crude Prevalence of Bipolar Disorder in Georgia Subpopulations* Several negative values observed in the "Other Race" subpopulations suggest higher prevalence rates of bipolar disorder. Asian subpopulations were very poorly represented by this data.



	White		Black or African American		Other Race		Asian	
Age Groups	Male Prev. (%)	Female Prev. (%)	Male Prev. (%)	Female Prev. (%)	Male Prev. (%)	Female Prev. (%)	Male Prev. (%)	Female Prev. (%)
0 - 9	0.43 (0.0)	0.36 (0.0)	0.37 (0.06)	0.31 (0.05)	0.23 (0.2)	0.18 (0.18)	N/A	N/A
10 - 19	3.67 (0.0)	6.45 (0.0)	2.6 (1.07)	3.79 (2.66)	3.57 (0.1)	4.28 (2.17)	0.78 (2.89)	1.65 (4.8)
20 - 29	6.43 (0.0)	7.75 (0.0)	7.02 (-0.59)	4.32 (3.43)	4.67 (1.76)	4.74 (3.01)	4.76 (1.67)	2.53 (5.22)
30 - 39	8.71 (0.0)	14.26 (0.0)	6.62 (2.09)	7.82 (6.44)	5.97 (2.74)	7.35 (6.91)	2.21 (6.5)	2.61 (11.65)
40 - 49	9.09 (0.0)	17.79 (0.0)	7.41 (1.68)	11.31 (6.48)	9.18 (-0.09)	14.52 (3.27)	3.02 (6.07)	5.8 (11.99)
50 - 59	8.28 (0.0)	14.41 (0.0)	7.06 (1.22)	11.41 (3.0)	9.24 (-0.96)	16.36 (-1.95)	N/A	8.82 (5.59)
60 - 69	4.8 (0.0)	7.12 (0.0)	3.85 (0.95)	5.16 (1.96)	6.12 (-1.32)	10.57 (-3.45)	1.27 (3.53)	2.31 (4.81)
70 - 79	2.93 (0.0)	3.91 (0.0)	1.52 (1.41)	2.11 (1.8)	2.09 (0.84)	3.9 (0.01)	1.07 (1.86)	1.69 (2.22)
80 - 89	2.82 (0.0)	3.63 (0.0)	1.93 (0.89)	1.94 (1.69)	1.25 (1.57)	2.35 (1.28)	N/A	2.11 (1.52)

Crude Prevalence of Depression in Georgia Subpopulations* In the "Other Race" subpopulations, some negative values are observed. Calculated metrics across subpopulations were reported for nearly every examined subpopulation.



	White		Black or African American		Other Race		Asian	
Age Groups	Male Prev. (%)	Female Prev. (%)	Male Prev. (%)	Female Prev. (%)	Male Prev. (%)	Female Prev. (%)	Male Prev. (%)	Female Prev. (%)
0 - 9	0.03 (0.0)	0.02 (0.0)	0.04 (-0.01)	0.02 (0.0)	0.04 (-0.01)	N/A	N/A	N/A
10 - 19	0.65 (0.0)	1.13 (0.0)	0.44 (0.21)	0.72 (0.41)	0.88 (-0.23)	1.06 (0.07)	N/A	0.29 (0.84)
20 - 29	1.09 (0.0)	0.58 (0.0)	1.49 (-0.4)	0.45 (0.13)	1.04 (0.05)	0.8 (-0.22)	N/A	N/A
30 - 39	1.24 (0.0)	1.05 (0.0)	1.38 (-0.14)	0.54 (0.51)	1.45 (-0.21)	0.99 (0.06)	N/A	0.59 (0.46)
40 - 49	1.12 (0.0)	1.19 (0.0)	1.46 (-0.34)	0.74 (0.45)	1.85 (-0.73)	1.61 (-0.42)	N/A	N/A
50 - 59	0.91 (0.0)	0.72 (0.0)	1.09 (-0.18)	0.71 (0.01)	1.26 (-0.35)	1.35 (-0.63)	N/A	N/A
60 - 69	0.36 (0.0)	0.25 (0.0)	0.32 (0.04)	0.21 (0.04)	0.61 (-0.25)	0.49 (-0.24)	N/A	N/A
70 - 79	N/A	N/A	N/A	0.05 (N/A)	N/A	0.14 (N/A)	N/A	N/A
80 - 89	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A

Crude Prevalence of Depression in Georgia Subpopulations* Several negative values were observed for the "Other Race" subpopulations. Interestingly, several negative values for only the "Black or African American" male subpopulations is observed.

* Values in ()'s represent difference in prevalence rates between that subpopulation and its analogous white subpopulation. The more negative the value (highlighted red), the higher the compared subpopulation prevalence rate was observed. "N/A" values are those subpopulations that had to either be suppressed due to privacy considerations or were not represented in this data.

Conclusions

Based on this exploratory approach, Georgia Medicaid subpopulations with chronic mental illness could face inequitable conditions. Future work includes examining patients' follow-up to care patterns to assess access to care and diagnostic practices. Possible factors to be examined in this process could be smaller geographical regions, patient visit types, and other factors. Finally, scrutinizing overall representativeness or fairness in subpopulations from data such as this could be explored.

[1] R. Crosby, M. L. Wendel, R. C. Vanderpool, and B. R. Casey, *Rural populations and health: Determinants, disparities, and solutions*. John Wiley & Sons, 2012.
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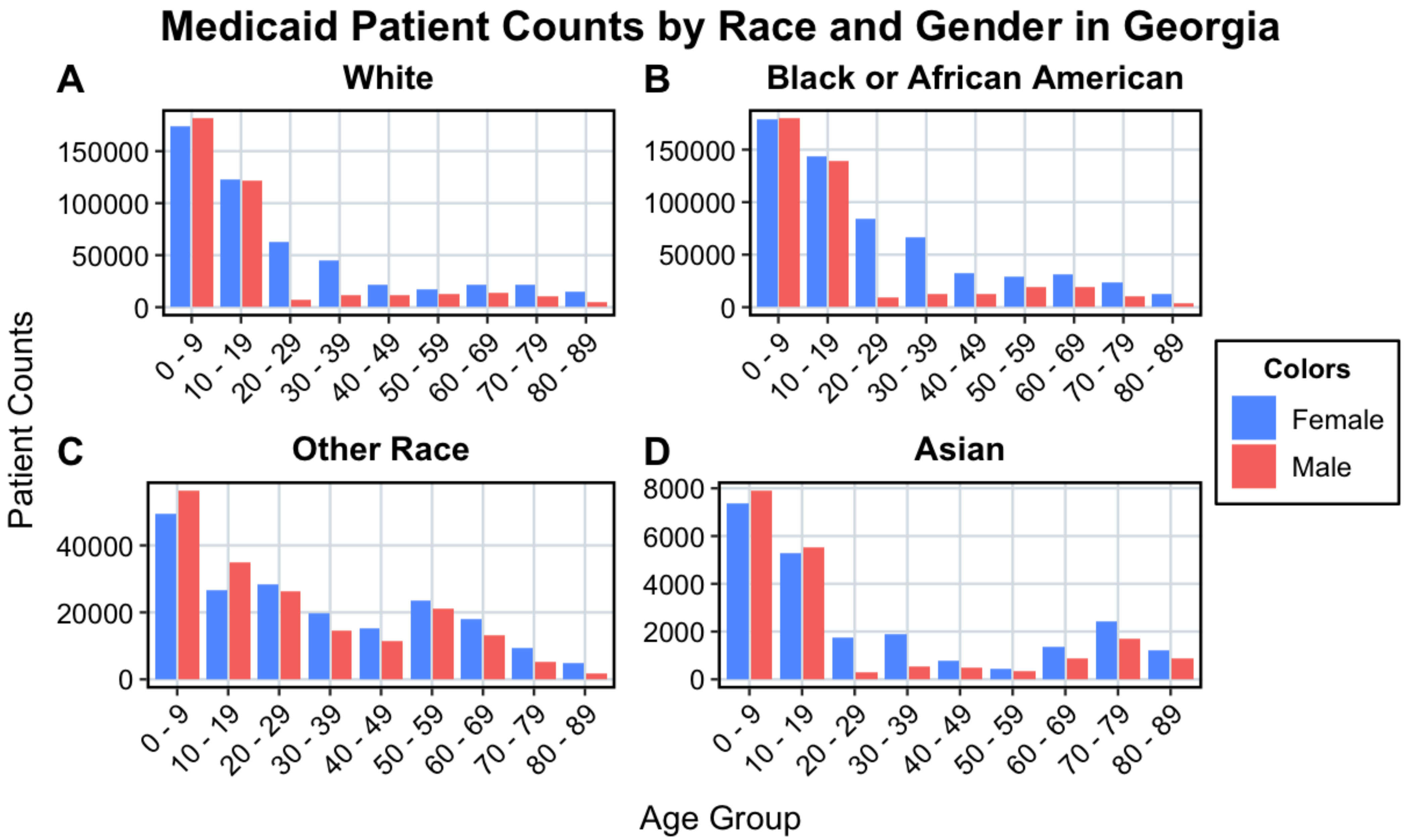
[3] S. L. Cutter, B. J. Boruff, and W. L. Shirley, “Social vulnerability to environmental hazards,” in *Hazards vulnerability and environmental justice*, Routledge, 2012, pp. 143–160.
[4] A. Soni, M. Hendryx, and K. Simon, “Medicaid expansion under the Affordable Care Act and insurance coverage in rural and urban areas,” *J. Rural Health*, vol. 33, no. 2, pp. 217–226, 2017.
[5] J. Warren and K. B. Smalley, “Rural public health: Best practices and preventive models,” 2014.
[6] L. Shi and G. D. Stevens, *Vulnerable populations in the United States*. John Wiley & Sons, 2021.
[7] D. M. Gray, A. Anyane-Yeboa, S. Balzora, R. B. Issaka, and F. P. May, “COVID-19 and the other pandemic: populations made vulnerable by systemic inequity,” *Nat. Rev. Gastroenterol. Hepatol.*, vol. 17, no. 9, pp. 520–522, Sep. 2020.
[8] W. C. Reeves *et al.*, “Mental illness surveillance among adults in the United States,” 2011.
[9] Centers for Disease Control and Prevention, “CDC/ATSDR Social Vulnerability Index 2018 Database US.”
[10] E. Jensen *et al.*, “The Chance That Two People Chosen at Random Are of Different Race or Ethnicity Groups Has Increased Since 2010,” United States Census Bureau, Aug. 2021. Accessed: Sep. 11, 2022. [Online].

Data Used

- 2.2 Million Medicaid Patients from Georgia

- 1999 – 2014 data range; ICD9; CMS Coding (OMB, etc.)

- CMS MAX Files used:
  - Personal Summary
  - Inpatient
  - Other Services
  - Prescription Drug



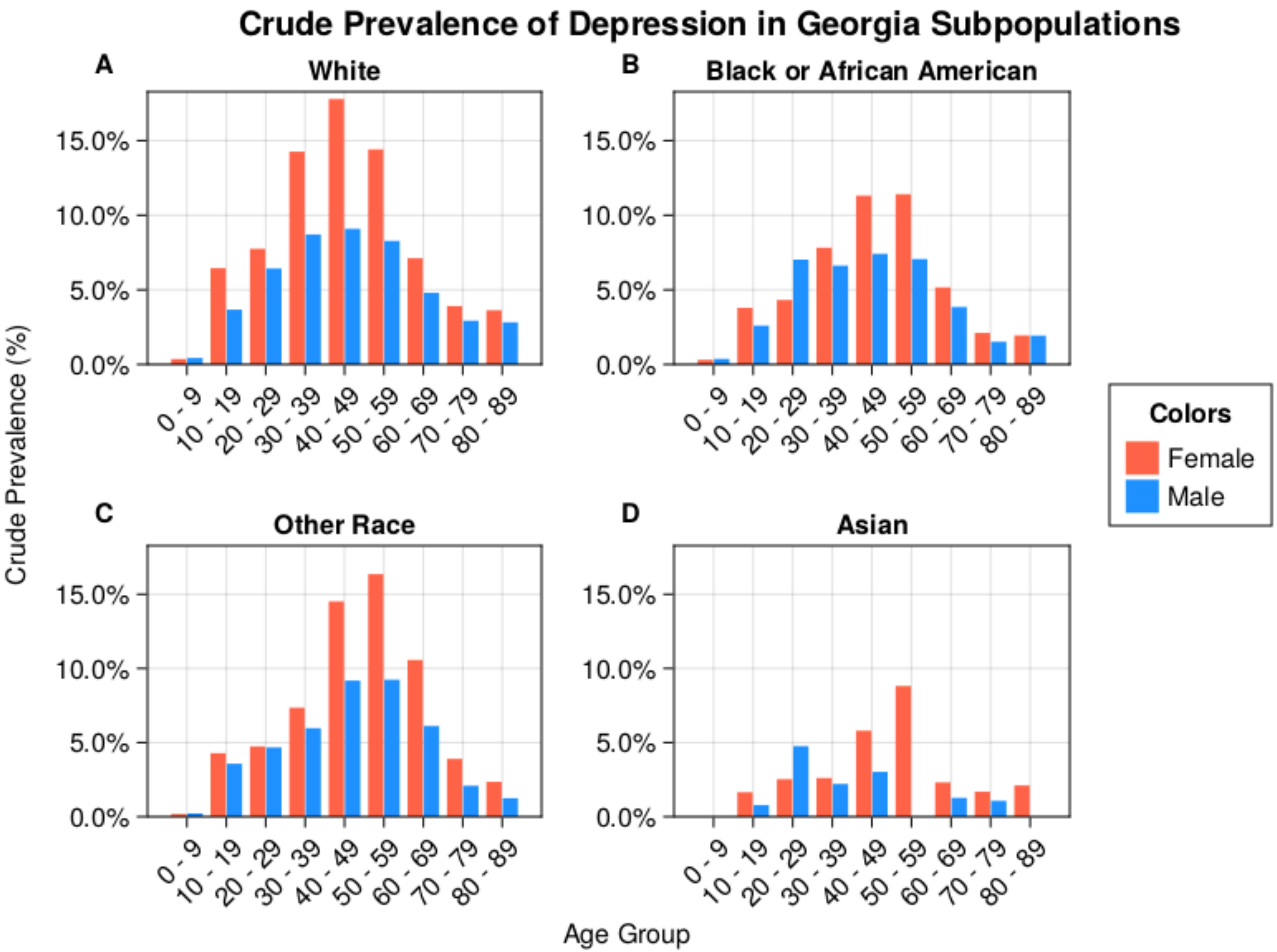
Medicaid Patient Counts by Race and Gender in Georgia
A
White
B
Black or African American
C
Other Race
D
Asian
Patient Counts
Age Group
0 - 9
10 - 19
20 - 29
30 - 39
40 - 49
50 - 59
60 - 69
70 - 79
80 - 89
0
50000
100000
150000
20000
40000
2000
4000
6000
8000
Colors
Female
Male

Methods

- Basic stratification algorithms
- Crude prevalence calculation

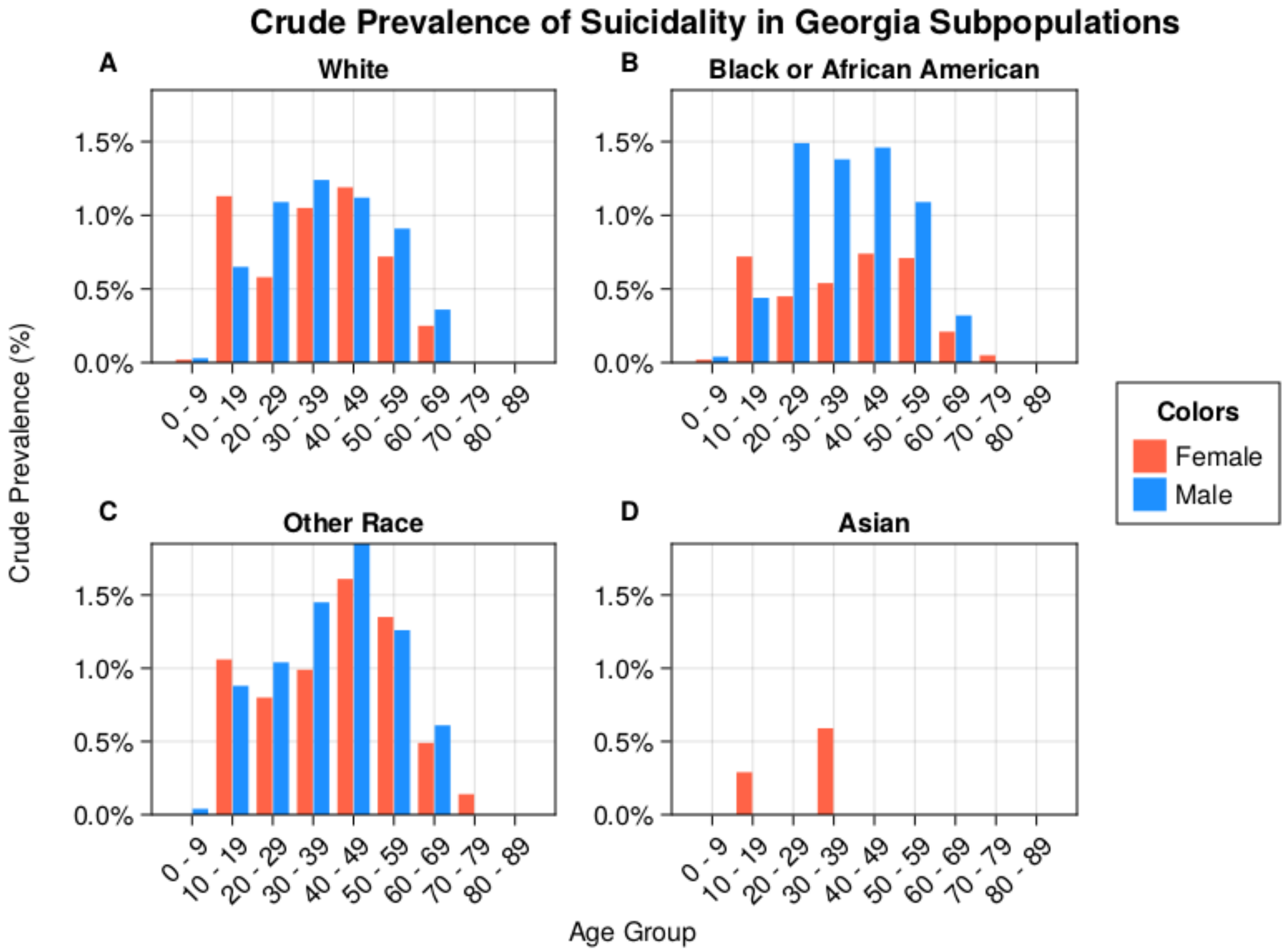
$$(1) \quad P = \frac{C + C_p}{N + N_p}$$

$$(2) \quad P = \frac{C}{N}$$



Crude Prevalence of Depression in Georgia Subpopulations
A
White
B
Black or African American
C
Other Race
D
Asian
15.0%
10.0%
5.0%
0.0%
0 - 9
10 - 19
20 - 29
30 - 39
40 - 49
50 - 59
60 - 69
70 - 79
80 - 89
Crude Prevalence (%)
Age Group
Colors
Female
Male

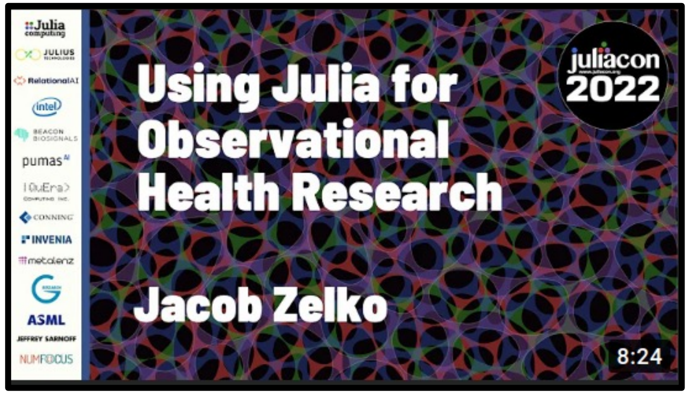
	White		Black or African American		Other Race		Asian	
Age Groups	Male Prev. (%)	Female Prev. (%)	Male Prev. (%)	Female Prev. (%)	Male Prev. (%)	Female Prev. (%)	Male Prev. (%)	Female Prev. (%)
0 - 9	0.43 (0.0)	0.36 (0.0)	0.37 (-13.95)	0.31 (-13.89)	0.23 (-46.51)	0.18 (-50.0)	N/A	N/A
10 - 19	3.67 (0.0)	6.45 (0.0)	2.6 (-29.16)	3.79 (-41.24)	3.57 (-2.72)	4.28 (-33.64)	0.78 (-78.75)	1.65 (-74.42)
20 - 29	6.43 (0.0)	7.75 (0.0)	7.02 (9.18)	4.32 (-44.26)	4.67 (-27.37)	4.74 (-38.84)	4.76 (-25.97)	2.53 (-67.35)
30 - 39	8.71 (0.0)	14.26 (0.0)	6.62 (-24.0)	7.82 (-45.16)	5.97 (-31.46)	7.35 (-48.46)	2.21 (-74.63)	2.61 (-81.7)
40 - 49	9.09 (0.0)	17.79 (0.0)	7.41 (-18.48)	11.31 (-36.42)	9.18 (0.99)	14.52 (-18.38)	3.02 (-66.78)	5.8 (-67.4)
50 - 59	8.28 (0.0)	14.41 (0.0)	7.06 (-14.73)	11.41 (-20.82)	9.24 (11.59)	16.36 (13.53)	N/A	8.82 (-38.79)
60 - 69	4.8 (0.0)	7.12 (0.0)	3.85 (-19.79)	5.16 (-27.53)	6.12 (27.5)	10.57 (48.46)	1.27 (-73.54)	2.31 (-67.56)
70 - 79	2.93 (0.0)	3.91 (0.0)	1.52 (-48.12)	2.11 (-46.04)	2.09 (-28.67)	3.9 (-0.26)	1.07 (-63.48)	1.69 (-56.78)
80 - 89	2.82 (0.0)	3.63 (0.0)	1.93 (-31.56)	1.94 (-46.56)	1.25 (-55.67)	2.35 (-35.26)	N/A	2.11 (-41.87)

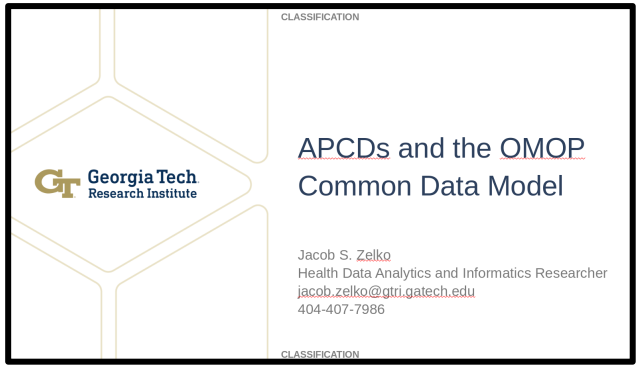

Crude Prevalence of Suicidality in Georgia Subpopulations
A
White
B
Black or African American
C
Other Race
D
Asian
Crude Prevalence (%)
1.5%
1.0%
0.5%
0.0%
0 - 9
10 - 19
20 - 29
30 - 39
40 - 49
50 - 59
60 - 69
70 - 79
80 - 89
Age Group
Colors
Female
Male

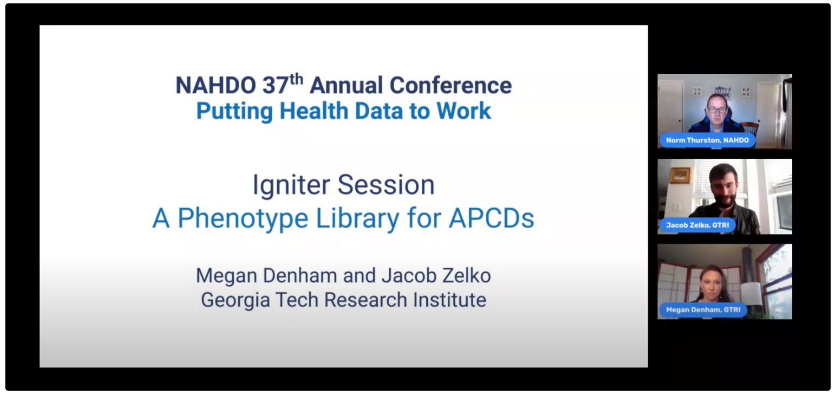
	White		Black or African American		Other Race		Asian	
Age Groups	Male Prev. (%)	Female Prev. (%)	Male Prev. (%)	Female Prev. (%)	Male Prev. (%)	Female Prev. (%)	Male Prev. (%)	Female Prev. (%)
0 - 9	0.03 (0.0)	0.02 (0.0)	0.04 (33.33)	0.02 (0.0)	0.04 (33.33)	N/A	N/A	N/A
10 - 19	0.65 (0.0)	1.13 (0.0)	0.44 (-32.31)	0.72 (-36.28)	0.88 (35.38)	1.06 (-6.19)	N/A	0.29 (-74.34)
20 - 29	1.09 (0.0)	0.58 (0.0)	1.49 (36.7)	0.45 (-22.41)	1.04 (-4.59)	0.8 (37.93)	N/A	N/A
30 - 39	1.24 (0.0)	1.05 (0.0)	1.38 (11.29)	0.54 (-48.57)	1.45 (16.94)	0.99 (-5.71)	N/A	0.59 (-43.81)
40 - 49	1.12 (0.0)	1.19 (0.0)	1.46 (30.36)	0.74 (-37.82)	1.85 (65.18)	1.61 (35.29)	N/A	N/A
50 - 59	0.91 (0.0)	0.72 (0.0)	1.09 (19.78)	0.71 (-1.39)	1.26 (38.46)	1.35 (87.5)	N/A	N/A
60 - 69	0.36 (0.0)	0.25 (0.0)	0.32 (-11.11)	0.21 (-16.0)	0.61 (69.44)	0.49 (96.0)	N/A	N/A
70 - 79	N/A	N/A	N/A	0.05 (N/A)	N/A	0.14 (N/A)	N/A	N/A
80 - 89	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A

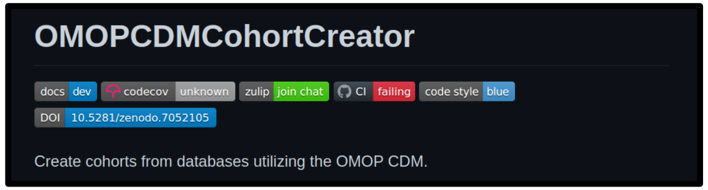
Project Impact

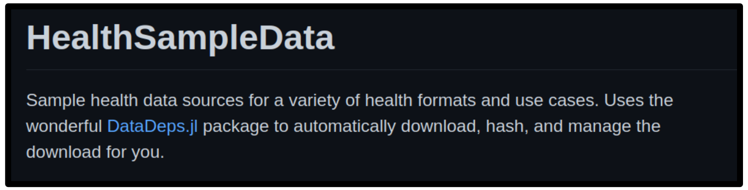
- Conferences
  - JuliaCon 2022
  - OHDSI Symposium 2022
  - NAHDO Conference 2022
- Outcomes
  - Award nominations
  - Partnerships
  - Paper drafts
  - Novel research tooling



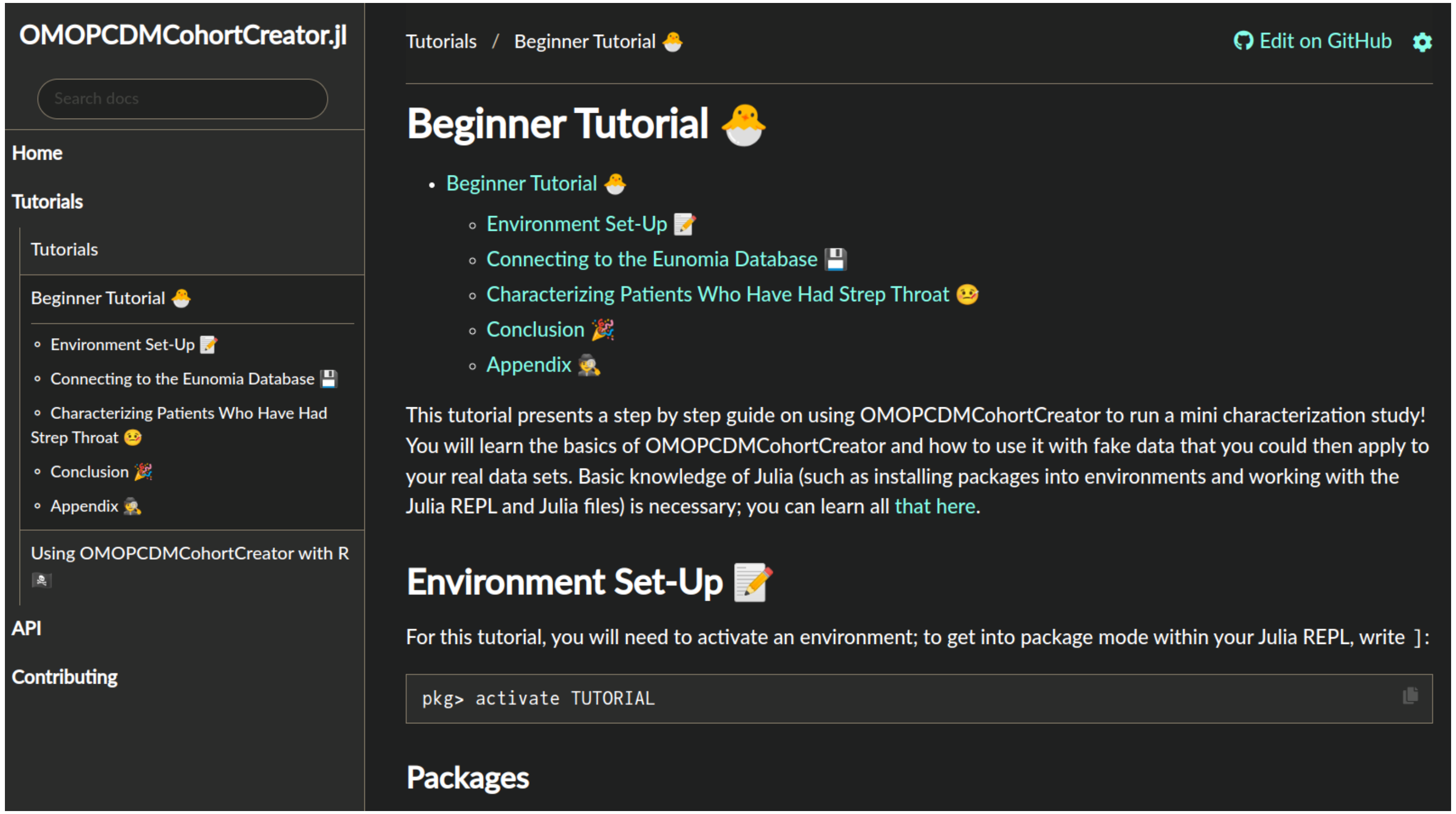








Project Impact



Beginner Tutorial 🐣

- Beginner Tutorial 🐣
  - Environment Set-Up 📝
  - Connecting to the Eunomia Database 💾
  - Characterizing Patients Who Have Had Strep Throat 😕
  - Conclusion 🎉
  - Appendix 🕵

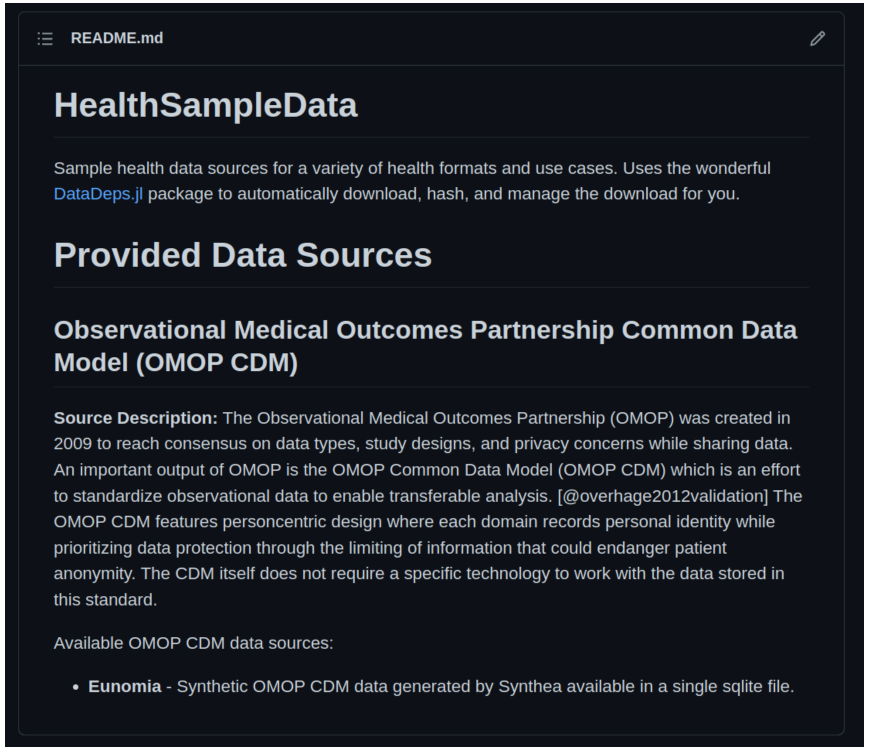
This tutorial presents a step by step guide on using OMOPCDMCohortCreator to run a mini characterization study! You will learn the basics of OMOPCDMCohortCreator and how to use it with fake data that you could then apply to your real data sets. Basic knowledge of Julia (such as installing packages into environments and working with the Julia REPL and Julia files) is necessary; you can learn all that here.

Environment Set-Up 📝

For this tutorial, you will need to activate an environment; to get into package mode within your Julia REPL, write `]`:

```
pkg> activate TUTORIAL
```

Packages



HealthSampleData

Sample health data sources for a variety of health formats and use cases. Uses the wonderful DataDeps.jl package to automatically download, hash, and manage the download for you.

Provided Data Sources

Observational Medical Outcomes Partnership Common Data Model (OMOP CDM)

Source Description: The Observational Medical Outcomes Partnership (OMOP) was created in 2009 to reach consensus on data types, study designs, and privacy concerns while sharing data. An important output of OMOP is the OMOP Common Data Model (OMOP CDM) which is an effort to standardize observational data to enable transferable analysis. [@overhage2012validation] The OMOP CDM features personcentric design where each domain records personal identity while prioritizing data protection through the limiting of information that could endanger patient anonymity. The CDM itself does not require a specific technology to work with the data stored in this standard.

Available OMOP CDM data sources:

- **Eunomia** - Synthetic OMOP CDM data generated by Synthea available in a single sqlite file.

Next Steps

- Deploy network studies at Partner Sites
- Expand Baseline & Follow-up Characterization
- Determine best approach in composite analyses
- Work on formalizing further definitions

Confirmed Data Partners

- Tufts Medical Center
    - Tufts Medical Center Data
        - 1.2M patients
    - Wellforce
- N3C COVID database
    - Securing access
    - 16M patients
- Georgia Tech Research Institute
    - CMS claims data
    - ~40M patients
- Boston Medical Center
    - 2M patients
- Ajou University
    - 1.5M patients
    - National data access: 20M+ patients

Ways to Get Involved!

- Become a data partner!
- Assist in creating chronic mental illness phenotype definitions
- Discuss final analyses approaches!

Questions?

OHDSI Teams!

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