Racial/Ethnic Disparities in COVID Treatment/Hospitalization: Social Determinants & Special Populations

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Introduction

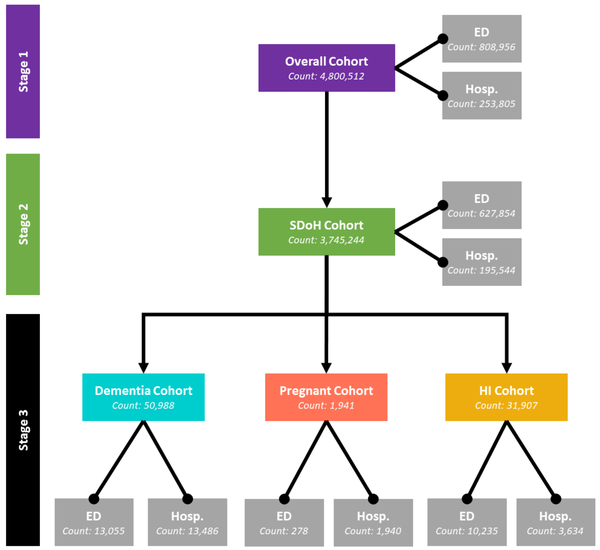
The COVID-19 pandemic has exposed long-standing inequities in health, both in access to healthcare systems and in the allocation of treatment once within those systems[1,2]. Numerous publications have shown the impact of social determinants of health (SDoH) on access and allocation[3,4], and it has been said an individual's ZIP code is greater than their genetic code as a predictor of their health[5].

- This study seeks to build off previous research[6] establishing clear racial/ethnic disparities in health access/treatment while solely looking at individual-level factors (age, sex, race/ethnicity, and medical comorbidities).
- We include SDoH data[7] and elucidate whether results are influenced by ecological-level predictors.
- We further examine differences in health equity across race/ethnicity within special, vulnerable populations

To that end, we utilized the National Covid Cohort Collaborative (N3C)[8,9]; as one of the largest national repositories of harmonized clinical data, N3C serves as a vast platform for researchers to study patterns in big health data.

Methods

Beginning with the entire N3C cohort, we filtered to only the patients who were COVID-positive. Our work consisted of three stages…



Brief descriptive analysis examined our overall cohort and special populations, looking at proportions of race/ethnicity and sex, as well as age distributions. Model analysis was conducted utilizing generalized estimating equation (GEE) models[10,11], allowing us to control for site-level bias from the different institutions that are sending in health data. QIC metrics were utilized for model evaluation[12]. Heavily skewed SDoH variables were adjusted for with Z-score transformations. The overall cohort and special populations were further split into those with ED visits and those with hospitalization (±7 days of COVID positivity). Outcome variables were…

- <u>ED visit group:</u> **(1)** hospitalization within 30 days of ED visit, and **(2)** patient death
- <u>Hospitalization group:</u> **(1)** Remdesivir, **(2)** ECMO, **(3)** systemic corticosteroids, and had **(4)** patient death during hospitalization

Research Questions

Our main question looked at an overall cohort of COVID+ individuals:

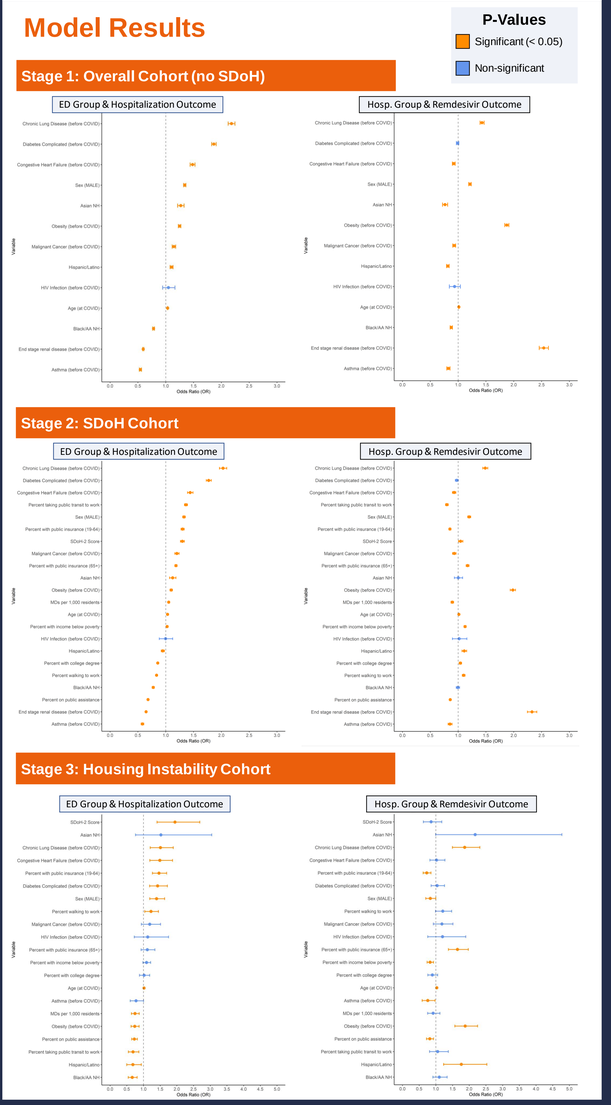
1. In a cohort of COVID+ individuals, is there health equity in hospitalization after an emergency department (ED) visit and, once hospitalized, in receiving treatment across race/ethnicity and social determinants of health (SDoH), after controlling for age, sex, and comorbidities?

We then asked the same question about the COVID+ individuals in the following special, vulnerable population:

2. Those who are experiencing housing instability (HI)

Further exploratory, descriptive analysis was conducted with other special populations – notably, **those with dementia** (including Alzheimer's), and **those who are pregnant**…

Model Results



Counts & Demographics

Table 1. Patient Counts/Proportions across Cohorts

Factor	Stage 1	Stage 3		
	Overall	Housing Unstable	Dementia	Pregnancy
Race/Ethnicity: n (%)				
Asian NH	26245 (2.69%)	118 (0.82%)	847 (2.86%)	116 (3.58%)
Black/AA NH	228979 (23.44%)	4539 (31.71%)	5835 (19.72%)	798 (24.66%)
Hispanic/Latino	145233 (14.87%)	1186 (8.28%)	2462 (8.32%)	1237 (38.23%)
White NH	576330 (59.0%)	8473 (59.19%)	20448 (69.1%)	1085 (33.53%)
Sex; n (%)				
Female	525375 (53.79%)	6505 (45.44%)	16900 (57.11%)	3236 (100%)
Male	451412 (46.21%)	7811 (54.56%)	12692 (42.89%)	–

** Counts are ED and Hosp. groups combined, not total patient counts*
*** Patients without SDoH data were not removed from counts in this table, values will not match with final counts shown in flow chart (see Methods)*

Graphs & Plots

Fig. 1: Race/Ethnicity Proportions across Cohorts

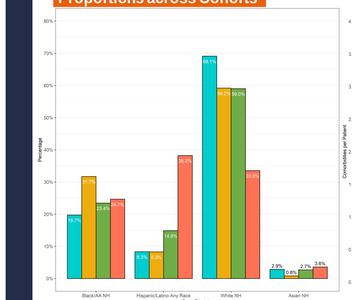


Fig. 2: Average Comorbidities per Patient across Race/Ethn. & Cohorts

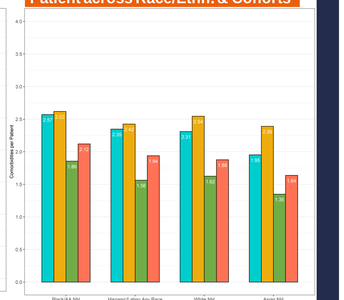
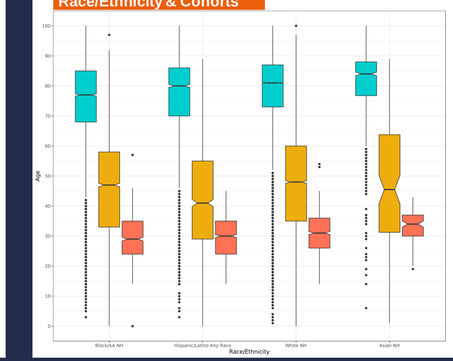


Fig. 3: Age Boxplots across Race/Ethnicity & Cohorts



Discussion

Overall Cohort (no SDoH)

- Asian and Hispanic/Latino patients have higher odds of being hospitalized after an ED visit, but are less likely to receive Remdesivir after hospitalization, compared to White patients. Black/AA patients have lower odds of being hospitalized after an ED visit and receiving Remdesivir once hospitalized
- Patients with chronic lung disease and obesity have higher odds of hospitalization and receiving Remdesivir. Those with congestive heart failure and malignant cancer have higher odds of hospitalization but lower odds of Remdesivir treatment, and those with end stage renal disease have lower odds of hospitalization but higher odds of treatment. Patients with asthma have lower odds of hospitalization and receiving Remdesivir

SDoH Cohort

- Compared to White patients, Hispanic/Latino patients have lower odds of hospitalization but are more likely to receive Remdesivir once hospitalized. Asian patients have higher odds of being hospitalized but non-significant odds of receiving Remdesivir. Black/AA patients have lower odds of hospitalization after an ED visit but are not significantly different in their odds of receiving remdesivir
- Percent with public insurance (65+) is tied with higher odds of hospitalization and receiving Remdesivir. Percent with public insurance (19-64) is tied with higher odds of being hospitalized but lower odds of receiving Remdesivir once hospitalized
  - Differences possibly due to the nature of public insurance (Medicare vs. Medicaid), age may also play role
- Percent with income below poverty was associated with greater odds of being hospitalized and receiving Remdesivir after hospitalization. On the other hand, percent on public assistance was tied to lower odds of hospitalization and receiving remdesivir

Housing Instability Cohort

- Hispanic/Latino and Black/AA patients had lower odds of getting hospitalized; however, once hospitalized, Hispanic/Latinos had higher odds of receiving Remdesivir, while Black/AAs ORs were not significantly different from White patients. Asian patients were not significantly different from the White patients for both odds of hospitalization and receiving Remdesivir
- Percent on public assistance was associated with lower odds of hospitalization and receiving Remdesivir; meanwhile, percent with public insurance (19-64) was tied to higher odds of hospitalization after an ED visit but lower odds of receiving Remdesivir once hospitalized

Conclusions

- Across all three cohorts, chronic lung disease and obesity are consistently significant factors in odds of hospitalization and receiving Remdesivir
- Across all three cohorts, Black/AAs consistently have lower odds of hospitalization after an ED visit
- When not considering SDoH, race/ethnicity plays significant role in odds of hospitalization and receiving Remdesivir; after including SDoH, race/ethnicity remains significant in odds of hospitalization but generally becomes non-significant in receiving treatment once hospitalized
  - SDoH factors remain significant in both odds of hospitalization and receiving Remdesivir
- Housing Instability cohort follows similar pattern to the SDoH cohort, however smaller size resulted in greater uncertainty and wider confidence intervals

Limitations

- Harmonized data from multiple institutions, may result in site-bias; attempted to control this through GEE models
- Small sample sizes in special population sub-cohorts (particularly pregnancy), may result in unrepresentative groups and skew results
- Housing instability data inconsistently collected and reported by health institutions
- Ecological fallacy: must be careful when drawing conclusions with the nature of our data (SDoH data collected at ecological-level, while patient medical data are collected at individual-level)

Future Work

- Applying Bayesian models to data

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