

# The Synergistic Effects of Social Determinants of Health and Race-Ethnicity on 30-Day Readmission Disparities in an Inpatient Population

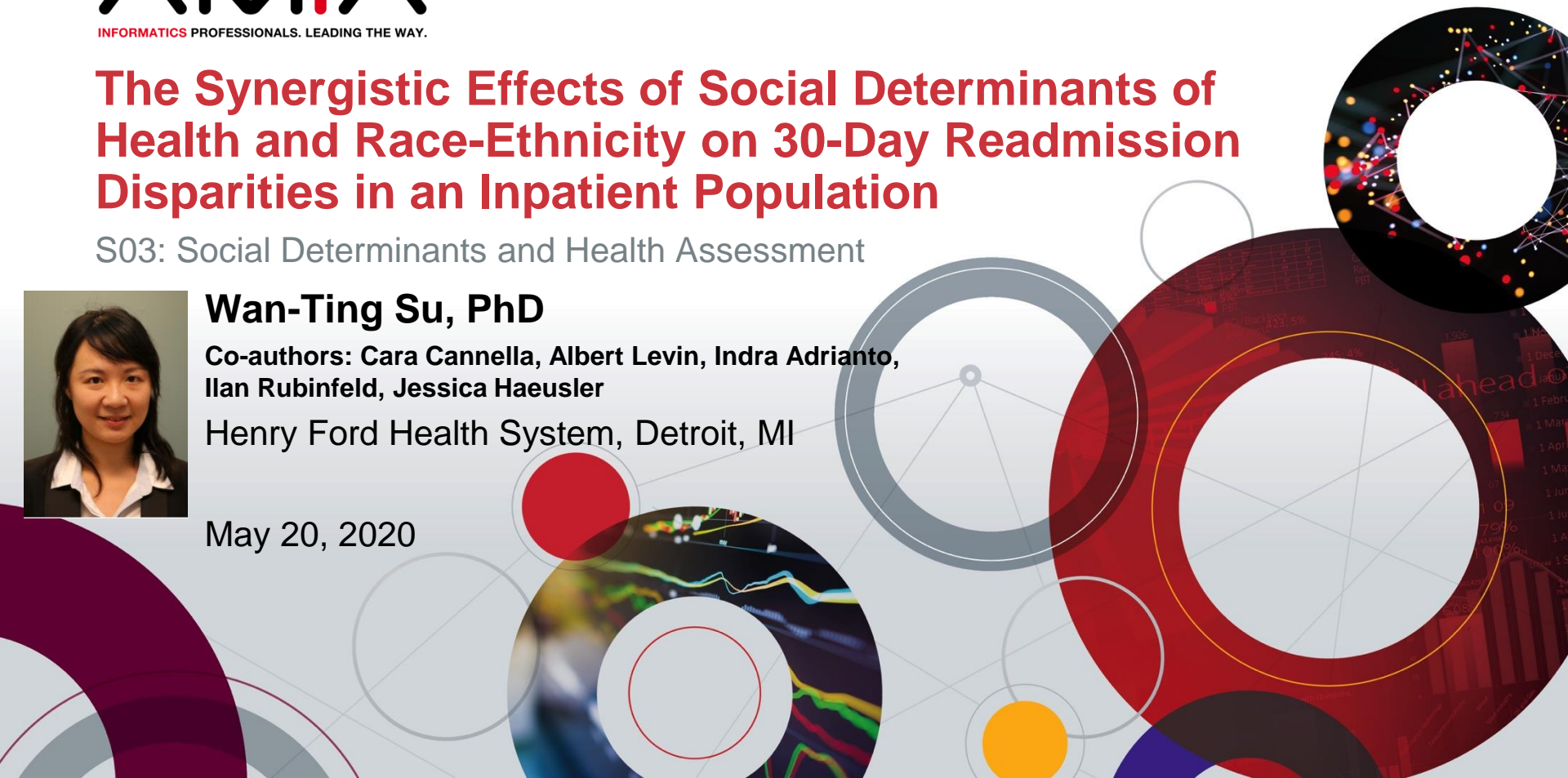
S03: Social Determinants and Health Assessment

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Ilan Rubinfeld, Jessica Haeusler

Henry Ford Health System, Detroit, MI

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# Disclosure

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I have no relevant financial relationships with commercial interests to disclose

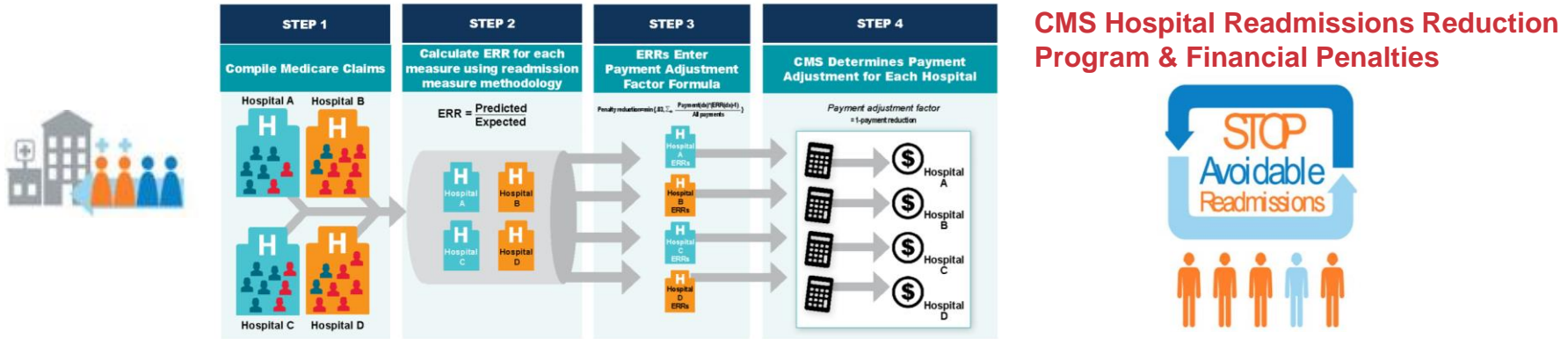
# Learning Objectives

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After participating in this session, the audience should be better able to understand:

- how the combination of social determinants of health (SDOH) and race-ethnicity impact disparities in 30-day readmission
- how multiple analytic methods can be applied and how risk factors can be used to identify groups of patients with varying levels of readmission risk

# Introduction



Sources: CMS (2017) HRRP User Guide; Edward Hunt (2016), Ponce Research Institute

- Hospital readmission rates are often used as quality metrics for hospital reimbursements or penalties
- Reduction in hospital readmission rates has been a priority for improvement of healthcare quality and patient clinical outcomes
  - Identifying risk factors of readmission is critical for intervention

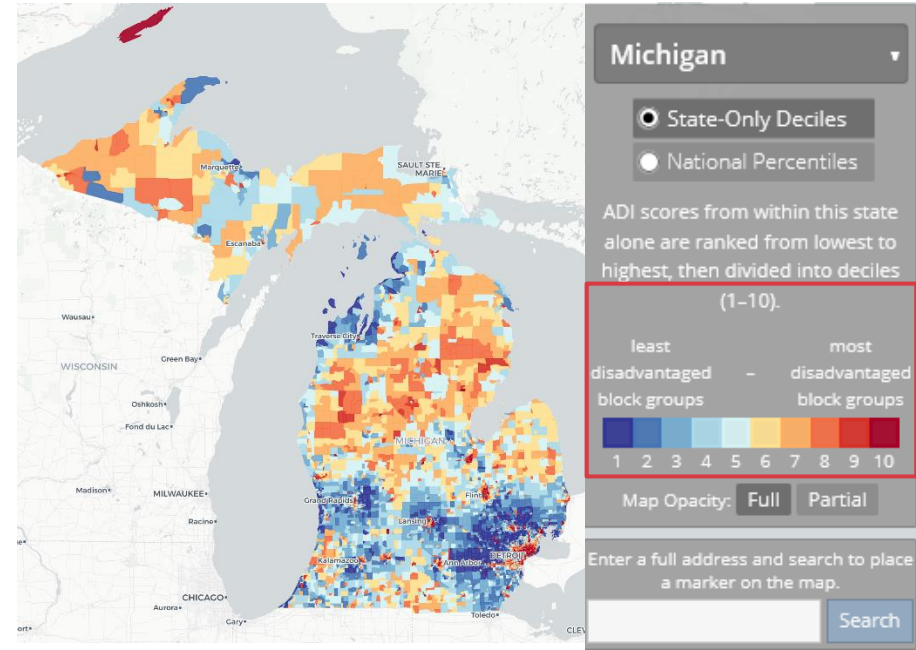
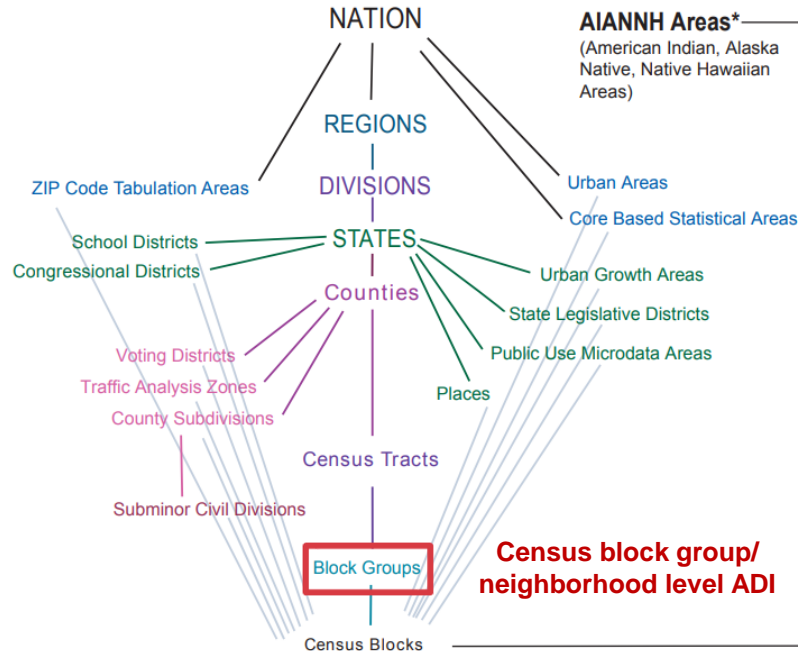
- Previous studies showed that race-ethnicity and the nonclinical conditions, SDOH,—including Area Deprivation Index (ADI)—were important factors that influence the likelihood of readmission
- SDOH: Centers for Disease Control and Prevention (CDC) defined as “The conditions in which people live, learn, work, and play affect a wide range of health risks and outcomes”



Sources: <https://www.healthypeople.gov/2020/topics-objectives/topic/social-determinants-of-health>

# Area Deprivation Index (ADI)

- A ranking measure of socioeconomic status disadvantage (income, education, employment, and housing quality)



Source: <https://www.neighborhoodatlas.medicine.wisc.edu/>

Source: United States Census Bureau

# Research Gap

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- There is a lack of research studying
  - the impact of SDOH and race-ethnicity on readmission risk in the broader population setting
  - how the effects of SDOH on readmission may depend upon race-ethnicity

# Objectives

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- Examine the effects of SDOH and race-ethnicity on readmission separately for all inpatient populations across a large health care system
- Investigate the racial-ethnicity specific effect of SDOH on readmission
- Identify groups of patients with differing readmission risk based on SDOH, race-ethnicity, and other covariates
- Locate potential geographical hotspots for high readmission risk



# Data: HFHS Inpatient Registry

- A retrospective study from 11/2015 - 12/2018

Data Source	Key Variable	Covariate Variable
<p>Primary Dataset</p> <ul style="list-style-type: none"><li>• Readmission Dataset from Epic EMR</li></ul> <p>Other Sources</p> <ul style="list-style-type: none"><li>• Flowsheet</li><li>• GIS Geocoding Software for ADI Mapping (ZIP+4)</li><li>• Diagnosis Table</li></ul>	<p>Race-Ethnicity<sup>[1]</sup></p> <p>SDOH</p> <ul style="list-style-type: none"><li>• Drug Use</li><li>• Lives Alone</li><li>• Depression</li><li>• ADI</li><li>• Primary Insurance Type</li><li>• Dual Eligible Coverage</li></ul> <p>Outcome</p> <ul style="list-style-type: none"><li>• 30-day Readmission</li></ul>	<ul style="list-style-type: none"><li>• Age</li><li>• Gender</li><li>• AHRQ CCSR Diagnosis Category<sup>[2]</sup></li><li>• Charlson Comorbidity Index (CCI)</li><li>• 17 Chronic Diseases</li></ul>

[1]: Black, White, Hispanic & Latino, Others; [2]: AHRQ Clinical Classifications Software Refined (CCSR) Categories

# Analytical Workflow

## Encounter-level Dataset

- 30-day Readmission Flag
- Race-Ethnicity
- Six SDOH
- Covariates

Q: What are the important SDOH?

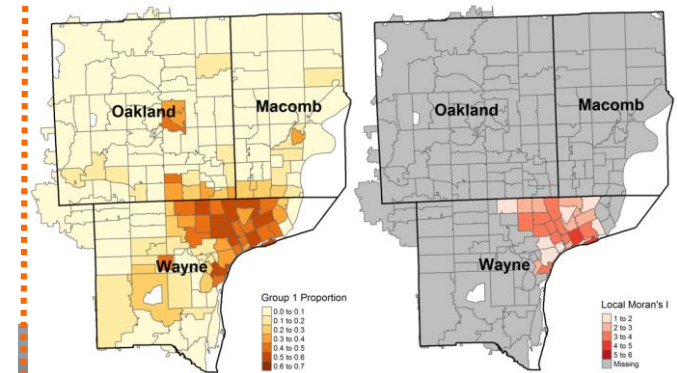
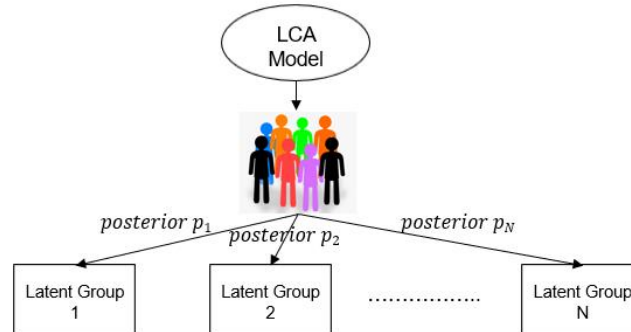
Q: How does the racial-ethnicity effect of SDOH affect readmission?

Univariate Analysis & Multivariable Logistic Regression

Q: How to identify groups of patients with varying levels of readmission risk and target on the high-risk group?

Q: How to detect the geographical hotspots for the high-risk group?

Latent Class Analysis (LCA) & Spatial Autocorrelation Analysis



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# Descriptive & Univariate Analysis

- Race-Ethnicity and all SDOH were significantly associated with 30-day readmission

**Total inpatient admissions:**  
256,077

**Primary outcome:**  
30-day readmission

158,574 unique patients

34,901 readmissions (13.6%)

Mean age 60  
years old with  
SD:19.7

57.7% female

63.0%  
White

27.0%  
Black

3.2%  
Hispanic



Variable	*** $P < 0.001$	Readmission-Yes	Readmission-No
Race-ethnicity, row%***			
White		0.13	0.87
African American		0.15	0.85
Hispanic		0.10	0.90
ADI Nat'l. Ranking, Mean***		67.68	65.08
Depression, row%***			
Depression History - Yes		0.17	0.83
Depression History - No		0.13	0.87
Insurance Type, row%***			
Medicare		0.17	0.83
Medicaid		0.11	0.89
Commercial		0.08	0.92

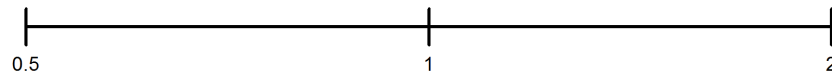
# The Effect of SDOH on Readmission

- Each SDOH was associated with readmission, except Medicaid insurance (vs. Medicare)

**Model A: Readmission Y/N ~ SDOH + Race-Ethnicity + Covariates\***

Pairwise Comparison	OR (95% CI)	P value
<b>Whole System</b>		
Drug Use	1.24 ( 1.18 - 1.31 )	<.001
Dual Eligible	1.22 ( 1.17 - 1.26 )	<.001
Depression	1.18 ( 1.14 - 1.22 )	<.001
Lives Alone	1.10 ( 1.07 - 1.14 )	<.001
Medicaid Insurance (vs. Medicare)	1.01 ( 0.96 - 1.06 )	0.710
Commercial Insurance (vs. Medicare)	0.83 ( 0.80 - 0.87 )	<.001

\*Covariates: Age + Gender + CCSR Diagnosis Category + Charlson CCI + Chronic Disease



# The Effects of Continuous & Categorical ADI on Readmission

- The patients living in more deprived areas (higher ADI) were more likely to be readmitted in 30 days

**Model A: Readmission Y/N ~ ADI (continuous/categorical) + other SDOH + Race-Ethnicity + Covariates\***




	Odds Ratio	95% CI	P-value
ADI (continuous)	1.002	1.000-1.002	$P < 0.001$
ADI (categorical)	Reference: ADI percentile Q1 (1-45)		
ADI Q2 (46-69)	1.07	1.03-1.11	$P < 0.001$
ADI Q3 (70-90)	1.07	1.03-1.10	$P < 0.001$
ADI Q4 (91-100)	<b>1.13</b>	1.08-1.17	$P < 0.001$

\*Age + Gender + CCSR Diagnosis Category + Charlson CCI + Chronic Diseases

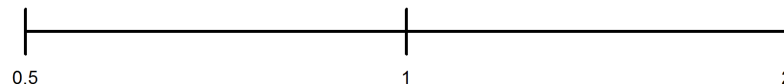
# The Racial-Ethnicity Specific Effect of SODH on Readmission

Model B: Readmission Y/N ~ SDOH + Race-Ethnicity + SDOH x Race-Ethnicity + Covariates\*

- The effect of depression on readmission was dependent upon race-ethnicity (Depression x Race-Ethnicity:  $p = 0.012$ )
  - The patients who had depression history were more likely to be readmitted in 30 days, especially for the Hispanic patients

Pairwise Comparison	OR (95% CI)	P value
<b>Depression</b>	"OR" are from three Race-Ethnicity stratified models	
Black		1.20 ( 1.12 - 1.28 ) <.001
White		1.15 ( 1.11 - 1.20 ) <.001
Hispanic		1.53 ( 1.23 - 1.89 ) <.001

\*Covariates: Age + Gender + CCSR Diagnosis Category + Charlson CCI + Chronic Disease



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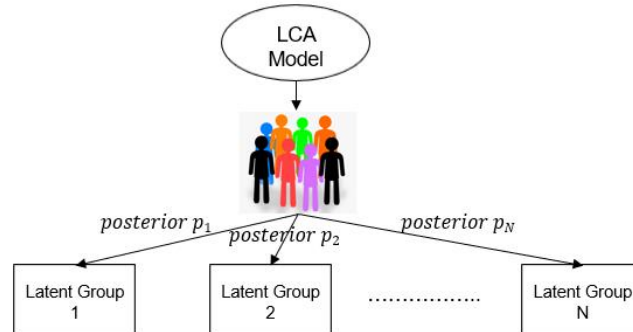
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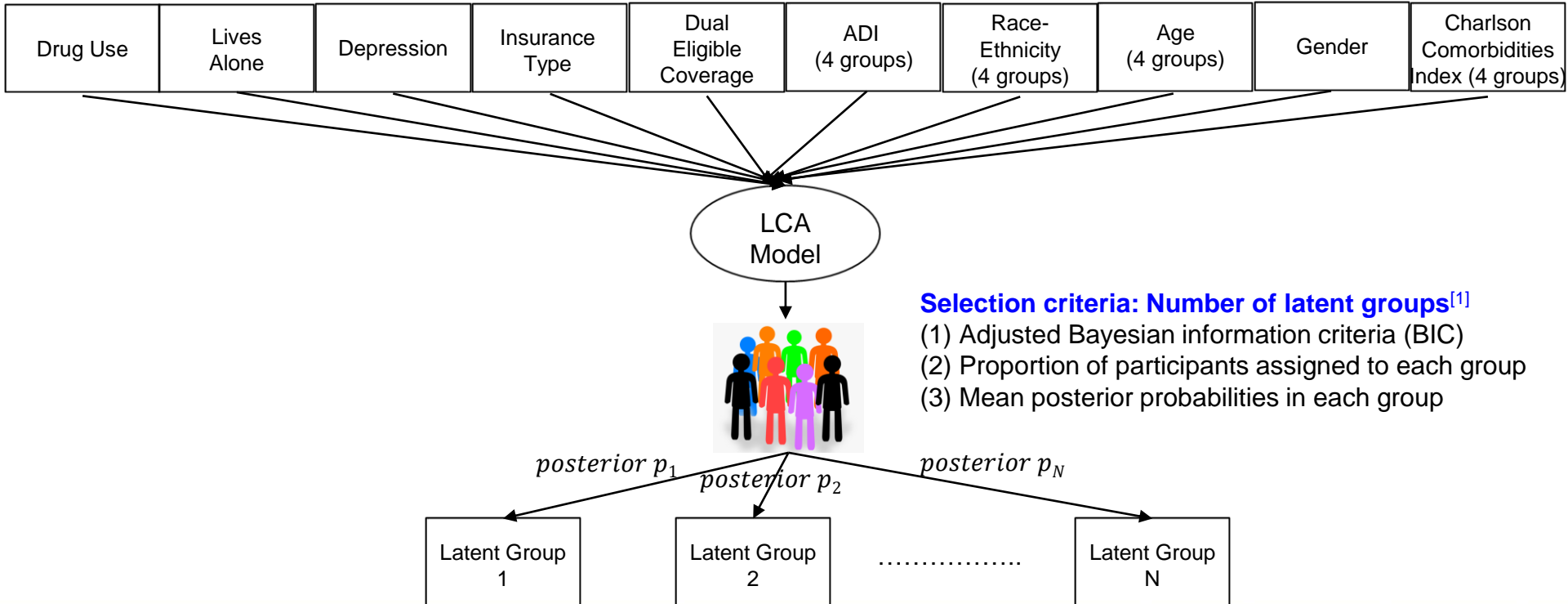
Latent Class Analysis (LCA) & Spatial Autocorrelation Analysis





# LCA Diagram

## Observed Variables



[1]: Muthén B, Muthén LK. Integrating person-centered and variable-centered analyses: Growth mixture modeling with latent trajectory classes. *Alcohol Clin Exp Res.* 2000;24(6):882–891

# LCA – Overall Summary

**Total Patient Encounters: 256,077**

**20% of Encounters**

**Group 1:  
High  
Readmission  
(19.5%)**

High proportions of

- African American
- High ADI
- Drug use
- Living alone
- Depression
- Dual Eligibility
- Medicare insurance

**35% of Encounters**

**Group 2:  
Medium  
Readmission  
(15.7%)**

High proportions of

- White patients
- Older patients
- Living alone
- Low ADI

**45% of Encounters**

**Group 3:  
Low  
Readmission  
(9.5%)**

High proportions of

- White patients
- Females
- Low comorbidity scores

Low proportions of

- All SDOH

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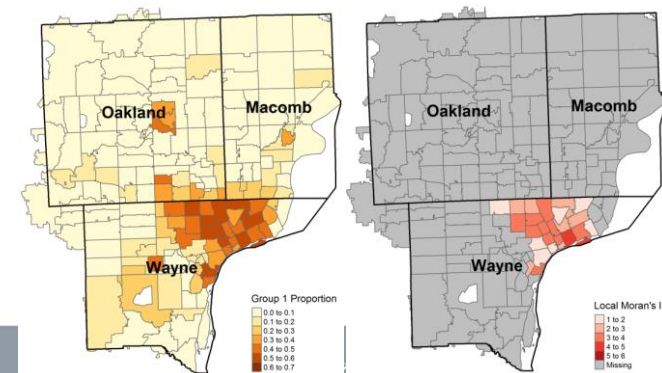
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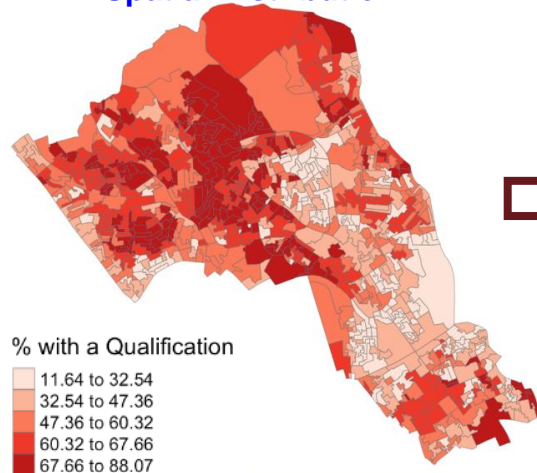
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# Spatial Analysis: Hot Spot Detection

- Analyze proportions of events that are located in geographical space
- Help understand the relationship between one object with other nearby objects
- Determine the location of clustering and dispersion

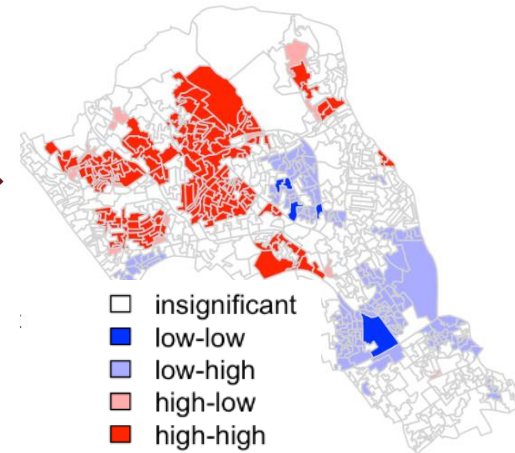
Spatial Distribution



Spatial Autocorrelation

**Spatial Statistics:**  
Local Moran Index  
**Spatial Autocorrelation Test**

Cluster and Outlier Map



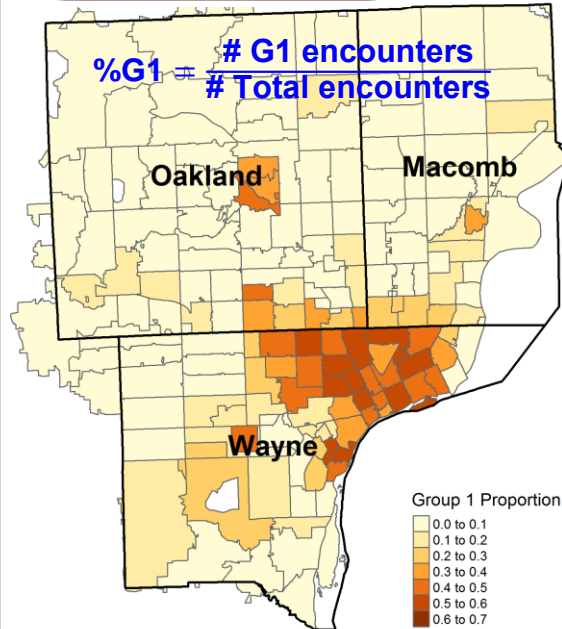
# Proportions of Patient Encounters from High-risk Readmission Group (Detroit Metropolitan Tri-County Area)

20% of Encounters

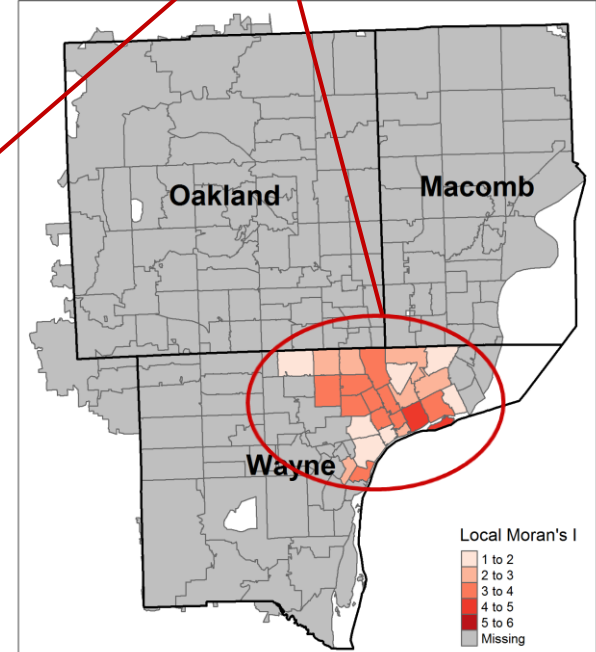
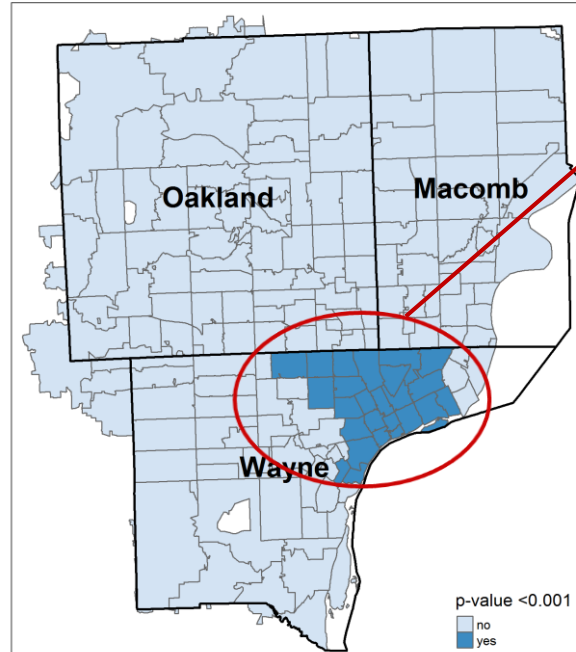
Group 1:  
High  
Readmission  
(19.5%)

- High proportions of
- African American
  - High ADI
  - Drug use
  - Living alone
  - Depression
  - Dual Eligibility
  - Medicare insurance

$$\%G1 = \frac{\# \text{ G1 encounters}}{\# \text{ Total encounters}}$$



**Hot Spots:** Detroit Cities (26 zip codes)  
**46% of high-risk encounters (G1) in hot spots**  
**9% of total encounters (20%\*46%) in hot spots**



# Limitations

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- The data source is limited to one health system
  - However, HFHS consists of 5 hospitals and serves a diverse population throughout the metro-Detroit area
- Readmission may be underestimated if patients readmitted outside of our health system
  - Supplementary admission data was included from Michigan Health Information Network (MiHIN) and Post Acute Referral Information in an attempt to mitigate the effects of this limitation

# Conclusion

- This study demonstrates the complex interplay between SDH and race-ethnicity influencing 30-day readmission
- Based on the identification of susceptible groups of patients, these results provide valuable information for prioritizing resource allocation within the health system
- Future work will leverage insight obtained from this study combined with additional SODH
  - Census data (healthcare access, transportation, etc.)
  - Social history (alcohol use, tobacco habits, etc.)

# Practical Application of this Session

- This study addresses the following topics:
  - Exploration of important features associated with readmission and the racial-ethnicity specific effect of SDOH on readmission
  - Identification of sub-populations with varying levels of readmission risk
  - Spatial analysis and the detection of potential high-risk group hotspots
- Health care organizations should be aware of patient populations that are at high risk of readmission
  - The enhancement of education and support for appropriate resource deployment provides opportunity to reduce readmission and improve overall healthcare quality



# Acknowledgments

- Virtual Data Warehouse team
  - Department of Public Health Sciences (PHS)
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Dr. Albert Levin  
(Scientist)



Dr. Indra Adrianto  
(Scientist)



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(Chief Quality Officer,  
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Jessica Haeusler  
(Sr. Performance  
Measurement Analyst)

# Thank you!

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