RISE OUT

RIsks and Socio-Ecological factors associated with Opioid Use Treatment

George Mason University
May 21, 2021

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Opioid Overdose Deaths Reach New Highs

Life expectancy in the U.S. dropped due to the increased rate of opioid overdose deaths.

Total opioid-related deaths rose again in 2019, one person dying every 10.7 minutes

66,813

$78 Billion

49,047 opioid-related deaths in 2019

10.7 minutes between deaths in 2019
Social-Ecological Model of Opioid Crisis

**Individual**
- People at risk for overdose
- Healthcare providers
- Family and friends
- Peer support groups
- Sponsors

**Interpersonal**
- Lack of stable housing
- Homelessness
- Availability of drugs
- Harm reduction programs

**Environment**
- Treatment teams
- Social service agencies
- Harm reduction programs

**Community and Organizations**
- Drug supply
- Funding sources
- Treatment options
- Social stigma

**Societal**
- Medication Assisted Treatment
- Naloxone distribution
- Harm reduction programs
- Criminal justice policies (e.g., Good Samaritan OD Law)
- Telehealth

**Policy**
- Medication Assisted Treatment
- Naloxone distribution
- Harm reduction programs
- Criminal justice policies (e.g., Good Samaritan OD Law)
- Telehealth
Geospatial Mapping
Spatiotemporal Analysis using Machine Learning & Multilevel Modeling
Patient & Provider Surveys
Geospatial Mapping
Takeaway

- Environmental and interpersonal treatment factors related to opioid use problem
- Disparities between counties in environmental treatment factors
- Interpersonal treatment factors are related to beliefs about treatment and treatment effectiveness
- More data is needed to further understand these relationships
Thank you!
Welcome!

- Thanks for joining us to talk about the opioid crisis!
- Please put any questions in the chat or hold them until the end for discussion.
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Our Team

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Nursing
Ph.D. Student
136 people die every day from an opioid overdose (including Rx and illicit opioids).

Over 70% of the nearly 71,000 drug overdose deaths in 2019 involved an opioid.

Three Waves of the Rise in Opioid Overdose Deaths

- Wave 1: Rise in Prescription Opioid Overdose Deaths - Started in 1999
- Wave 2: Rise in Heroin Overdose Deaths - Started in 2010
- Wave 3: Rise in Synthetic Opioid Overdose Deaths - Started in 2013

Nearly 73% of all opioid overdose deaths involve synthetic opioids (excluding methadone).

Environmental Factors & Opioid Overdoses
Data description

- Outcome variable: Emergency department (ED) visits for opioid OD
- Data from 2016 to 2019
- County-level predictors from publicly available datasets:
  - U.S. Census American Community Survey (poverty, health insurance)
  - Map the Meal Gap (food insecurity)
  - VA State Police Department (crimes against person)
  - VDH Health Opportunity Index
  - County Health Rankings.org
County-level analysis

● **Spatial analysis**
  ○ Use Moran’s I index to find spatial autocorrelation based on overdose rates
  ○ Build a classification model to classify counties into high or low opioid region based on their characteristics
    ■ Find most important predictors (risk factors or protective factors)

● **Temporal analysis**
  ○ Use Multi-level modeling to model overdose rate trend and their relationships with other variables
Spatial analysis: County-level disparities

- Use Moran’s I index to measure how a county is similar to its neighboring county
  - Also finds hotspots and coldspots
- Yellow dots mark the location of hospitals

Dark red = High overdose rate
Red = Clusters of high OD rate, Blue = Clusters of low OD rate
Spatial analysis: County-level disparities

- Use Moran’s index to measure how a county is similar to its neighboring county
  - Also finds **hotspots** and **coldspots**
- Yellow dots mark the location of hospitals

---

Opioid overdose rates - ED visits

- Dark red = High overdose rate

Hotspots and coldspots

- Red = Hotspots, Blue = Coldspots
Spatial analysis: Classification model

**Problem:**
- Understand why some counties have high overdose rates and others don’t
- Find contributing socio-economical, and environmental factors

**Solution:**
- Use a machine learning model that can also be used as feature selector
  - e.g. Random Forest Classifier
  - Classify the counties into low and high opioid overdose regions
  - Counties with higher than mean overdose rate = 1
  - Counties with lower or equal to mean overdose rate = 0
  - Get the most important predictors as returned by the model
Spatial analysis:
Classification results

Classifer details
- RandomForestClassifier
- Rule based classifier
- Feature importance plotted based on decrease in impurity

Classification results
Mean ROC AUC: 0.732
Mean Accuracy: 0.717
Mean F1: 0.726
Mean Precision: 0.726
Mean Recall: 0.726
Motivation for temporal analysis - 2016

Overdose rates change over time and so do the environmental factors
Motivation for temporal analysis - 2017

Overdose rates change over time and so do the environmental factors.
Motivation for temporal analysis - 2018

Overdose rates change over time and so do the environmental factors
Motivation for temporal analysis - 2019

Overdose rates change over time and so do the environmental factors
Temporal analysis: Multi-level modeling

**Motivation:**

- Understanding how different variables (e.g., crime and physical environment) change with respect to the change in overdose rates
- Can other static variables predict the overdose trend?
Temporal analysis: Multilevel Growth Models

- Ran Two-Level Growth Models
  Random growth model was best fit
- Outcome: Annual ED overdose rates (2016-2019)

<table>
<thead>
<tr>
<th>Level</th>
<th>Variables</th>
<th>Type of Variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level 1</td>
<td>Time-related</td>
<td>Timepoint</td>
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<tr>
<td></td>
<td>Year</td>
<td>Time varying covariate</td>
</tr>
<tr>
<td></td>
<td>Criminal Activity Against Persons</td>
<td>Time varying covariate</td>
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<tr>
<td></td>
<td>Physical Environment</td>
<td></td>
</tr>
<tr>
<td>Level 2</td>
<td>Person (i.e., county)-related</td>
<td>Main effects (Moderator) and interaction</td>
</tr>
<tr>
<td></td>
<td>LILA Food Access Index</td>
<td>effects (Time*Moderator)</td>
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<tr>
<td></td>
<td>Employment Access Index</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Walkability Index</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Population Weighted Density Index</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Poverty Rate</td>
<td></td>
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</table>
## Conditional Growth Model Results - ED Overdose Rate

<table>
<thead>
<tr>
<th>Variables</th>
<th>B (Standard Error)</th>
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<tbody>
<tr>
<td>Intercept</td>
<td>.006 (.082)</td>
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<tr>
<td>Year</td>
<td>-.0001 (0.03)</td>
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<tr>
<td><strong>Criminal Activity</strong></td>
<td><strong>.275 (.074)</strong>*</td>
</tr>
<tr>
<td>Physical Environment</td>
<td>1.46 (1.096)</td>
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<tr>
<td>Year*LILA Food Access</td>
<td>.031 (.031)</td>
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<tr>
<td>Year*Employment Access</td>
<td>.044 (.046)</td>
</tr>
<tr>
<td>Year*Walkability</td>
<td>-.061 (.057)</td>
</tr>
<tr>
<td>Year*Population Weighted Density</td>
<td>.017 (.053)</td>
</tr>
<tr>
<td>Year*Poverty Rate</td>
<td>.043 (.039)</td>
</tr>
</tbody>
</table>

Note. Main effects not shown (all were NS); *p < .01*
Interpersonal Treatment Factors
PROVIDER & PATIENT SURVEYS

- Demographics
- Clinical Practice
- Shared Decision Making
- Patient Engagement
- Stigma
Provider Survey

Practice Setting (n=41)

<table>
<thead>
<tr>
<th>Setting</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>Private Office</td>
<td>14</td>
</tr>
<tr>
<td>Hospital-based clinic</td>
<td>16</td>
</tr>
<tr>
<td>ED</td>
<td>1</td>
</tr>
<tr>
<td>Private SU Tx Program</td>
<td>2</td>
</tr>
<tr>
<td>Other</td>
<td>15</td>
</tr>
</tbody>
</table>

Licensed to Prescribe MAT

<table>
<thead>
<tr>
<th>X-waiver Status</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yes X-waiver</td>
<td>9</td>
</tr>
<tr>
<td>No X-waiver</td>
<td>39</td>
</tr>
</tbody>
</table>
Provider Survey

Substance Use Screening (n=41)

- Tobacco: 63%
- Alcohol: 66%
- Rx Pain Meds: 51%
- Illegally obtained Pain Meds: 48%
- Heroin: 34%
- Other illicitly obtained drugs: 53%
- Vaping: 41%
- None/Don’t ask
- IV Drug Use (somewhat or...)
- Don’t discuss SU unless patient...

Medications Prescribed

- Methadone: 2
- Buprenorphine: 2
- Naltrexone: 1
- Previously Rx MAT and stopped: 3
Provider Survey:  
Correlations

| Stigma (SDSS) and Shared Decision Making (SDMQ)  
n = 31 (p=.610) |
|------------------------------------------------|
| X-waiver and Shared Decision Making  
n=33 (p=109) |
| X-waiver and Stigma  
n=31 (p=.056) |
Patient Survey

- 36 participants
- Recruited from Bluelight, Reddit, and surrounding community
- Inclusion:
  - Currently misusing opioids OR in MAT
  - Adult
  - Living in United States
Opioid Use & Treatment Patterns

- Reasons for not using MAT: could not afford to see MAT provider (3), could not find MAT provider (2), not ready to stop using (2), family disapproves (3), requires painkillers (1), medical record (3), preferred non-MAT treatment (2)
## Characteristics of opioid use treatment

<table>
<thead>
<tr>
<th>Clinical Practices</th>
<th>MAT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Screening</td>
<td>72%</td>
</tr>
<tr>
<td>Discussion of risks</td>
<td>80%</td>
</tr>
<tr>
<td>Harm reduction counseling</td>
<td>40%</td>
</tr>
<tr>
<td>Respect/compassion</td>
<td>72%</td>
</tr>
<tr>
<td>Cultural sensitivity</td>
<td>52%</td>
</tr>
<tr>
<td>Family involvement</td>
<td>28%</td>
</tr>
<tr>
<td>Unconditional positive regard</td>
<td>72%</td>
</tr>
<tr>
<td>Opioid use as lifelong</td>
<td>54%</td>
</tr>
</tbody>
</table>
Are interpersonal treatment factors associated with patient perceptions of MAT?

MAT ($n = 25$)

- Patient perceptions of MAT safety
- Patient perceptions of MAT as a “drug free alternative”

- Shared decision making
- Provider involves family
- Provider unconditional support
- Shared decision making
- Provider discusses opioid use risks
Are interpersonal treatment factors associated with patient outcomes?

MAT (n = 25)

- MAT helped with treatment goals
- Opioid overdoses during MAT
- Provider discusses opioid use risk ($r = 0.51$, $p = 0.01$)
- Discussion of opioid use disorder as a lifelong disorder ($r = 0.74$, $p = 0.00$)
- Discussion of opioid use risks ($r = -0.45$, $p = 0.03$)
- Treatment with compassion, empathy and respect ($r = -0.46$, $p = 0.02$)
Takeaway

- Environmental and interpersonal treatment factors related to opioid use problem
- Disparities between counties in environmental treatment factors
- Interpersonal treatment factors are related to beliefs about treatment and treatment effectiveness
Limitations & Future Directions

- Lack of comprehensive data
  - Lack of linked data
  - Lack of granular data (e.g., neighborhood)
  - Lack of longitudinal data
- Difficulty obtaining data sharing agreements
- Challenges in original data collection
Thank you!

- CASBBI faculty
- Karen Raymond, Prince William County CSB
- Pamela Fine, Nursing, CHHS
- Nancy Spencer, Empowered Communities Opioid Project (ECOP)
- Katrina King, Empowered Communities Opioid Project (ECOP)
- Virginia Council of Nurse Practitioners
- Virginia Association of DNPs
- Mason and Partner clinicians
Questions?