Electronic Medical Record Phenotyping Accurately Identifies Opioid Use Disorder in the Emergency Department
Disclosures

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• This project is part of the Pragmatic Trial of User-Centered Clinical Decision Support to Implement EMergency Department-Initiated BuprenorphinE for Opioid Use Disorder (EMBED)
What’s the problem?

• Opioid Use Disorder (OUD) causes significant morbidity and mortality
  – Acute overdoses
  – Sequalae of chronic addiction
• Interventions can reduce M&M, but...
  – Require recognition of OUD
• Objective:
  – *Automated* identification of patients with OUD
  – Target population for future prospective interventions
Computable Phenotypes

- What is a computable phenotype?
  - “A defined set of data elements and logical expressions used to identify individuals or populations (i.e., cohorts) with particular diagnoses or medical conditions via clinical characteristics, events, and service patterns that are ascertained using a computerized query of an EHR system or data repository”
  - EHR data → automated identification of OUD patients

- Benefits:
  - Rapid identification of patients
  - Easy integration into automated alerts

Methods: Internal Validation

- **Study Setting**: large healthcare system (268,000+ visits/year)
  - Automated extraction from Epic EHR
  - November 1, 2017 to October 31, 2018
  - Inclusion: > 18 years of age
  - Exclusion: admitted, pregnant, on MOUD

- **EHR Definition**
  - Algorithm 1: Clinician or Biller coding
  - Algorithm 2: Keywords in chief complaint or reason for visit
    - “Heroin”, “Opiate”, “Opioid”, “Narcan”
    - Exclude: “alcohol”, “ETOH”, “Benzodiazepine”

- **Clinical (gold standard) definition of OUD**
  - Diagnostic and Statistical Manual of Mental Disorders, 5th Edition (DSM-5)
  - Two physician reviewers: *Cohen’s Kappa 0.95*
  - Third reviewer for reconciliation
## Results: Internal Validation

<table>
<thead>
<tr>
<th>Algorithm 1: 1508 + → random sample of 50 + 50 negative charts</th>
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<tbody>
<tr>
<td>Phenotype +</td>
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<td>Phenotype -</td>
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<table>
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<tr>
<th>Algorithm 2: 249 + → random sample of 25 + 25 negative charts</th>
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<td>Phenotype +</td>
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<tr>
<td>Phenotype -</td>
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Methods: External Validation

- **Study Setting:** second large healthcare system (200,000+ visits)

- **Main criteria:**
  - Automated extraction from Epic EHR
  - **20,000 Charts** from November 1, 2017 to October 31, 2018
  - Inclusion: > 18 years of age
  - Exclusion: admitted, pregnant, on MOUD

- **EHR Definition**
  - Algorithm 1: Clinician or Biller coding
  - Algorithm 2: Keywords in chief complaint or reason for visit
    - “Heroin”, “Opiate”, “Opioid”, “Narcan”
    - Exclude: “alcohol”, “ETOH”, “Benzodiazepine”

- **Clinical (gold standard) definition of OUD**
  - Diagnostic and Statistical Manual of Mental Disorders, 5th Edition (DSM-5)
  - Two physician reviewers: **Cohen’s Kappa 0.93**
  - Third reviewer for reconciliation
Results: External Validation

- 20,000 charts sampled in time frame
  - Algorithm 1: 55 identified
  - Algorithm 2: 1 identified
    - Combined for analysis
  - 0.25% random sample of remaining → 50 negative charts

<table>
<thead>
<tr>
<th>Reviewer +</th>
<th>Reviewer -</th>
<th>Predictive Value (95% CI)</th>
<th>Accuracy (95% CI)</th>
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</thead>
<tbody>
<tr>
<td>Phenotype +</td>
<td>53</td>
<td>3</td>
<td>PPV 0.95 (0.851-0.989)</td>
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<tr>
<td>Phenotype -</td>
<td>4</td>
<td>46</td>
<td>NPV 0.92 (0.807-0.978)</td>
</tr>
</tbody>
</table>
Discussion

• Conclusions:
  – Algorithms were accurate, within limits of sample population
  – External validity supports generalizability

• Limitations:
  – Inflated OUD prevalence
  – Small sample size

• Future Directions:
  – Apply prospectively to identify patients eligible for interventions
    • EMR integration → Automated “alerts”
  – Translate to additional healthcare systems
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