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 **EM**ergency Department-Initiated **B**uprenorphin**E** for Opioid Use **D**isorder (**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[1]"*
  - EHR data → automated identification of OUD patients
- Benefits:
  - Rapid identification of patients
  - Easy integration into automated alerts

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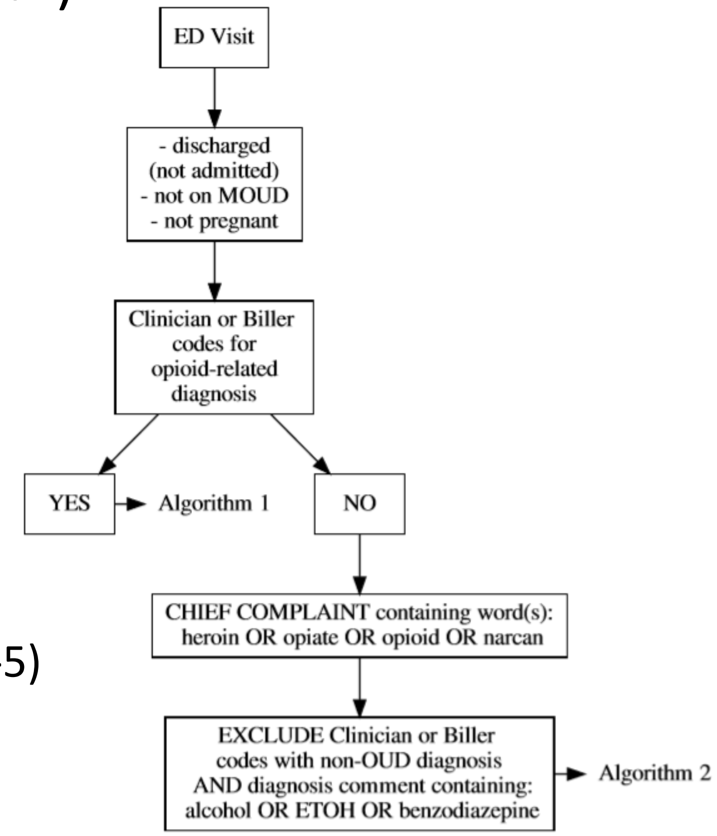
1. Richesson RL, Hammond WE, Nahm M, et al. Electronic health records based phenotyping in next-generation clinical trials: a perspective from the NIH Health Care Systems Collaboratory. J Am Med Inform Assoc. 2013;20(e2):e226-31.

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

	Reviewer +	Reviewer -	Predictive Value (95% CI)	Accuracy (95% CI)
Algorithm 1: 1508 + → random sample of 50 + 50 negative charts				
Phenotype +	48	2	PPV 0.96 (0.862-0.995)	0.97 (0.915-0.994)
Phenotype -	1	49	NPV 0.98 (0.894-0.999)	

Algorithm 2: 249 + → random sample of 25 + 25 negative charts				
Phenotype +	20	5	PPV 0.8 (0.593-0.932)	0.90 (0.782-0.967)
Phenotype -	0	25	NPV 1.0 (0.863-1*)	

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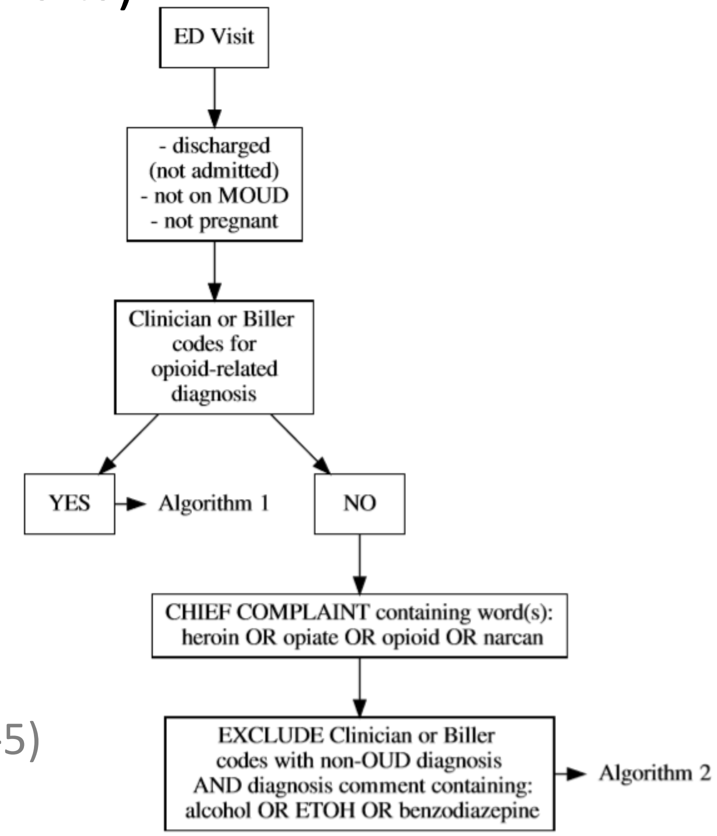
Methods: External Validation

- 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



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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

	Reviewer +	Reviewer -	Predictive Value (95% CI)	Accuracy (95% CI)
Combined algorithms:				
Phenotype +	53	3	PPV 0.95 (0.851-0.989)	0.93 (0.869-0.973)
Phenotype -	4	46	NPV 0.92 (0.807-0.978)	

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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