Predictive models to assess risk of developing opioid use disorder: a systematic review

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Background

Opioid use disorder (OUD):
- affects more than 16 million people worldwide [1]
- costs the US more than 78 billion dollars/year [1]
- contributes greatly to opioid overdose (OD) and death [2]

Predictive analytics can help develop accurate clinical decision support systems to identify high-risk individuals and facilitate access to care.

Objective

This systematic review aims to consolidate evidence on the feasibility, efficacy, and accuracy of using predictive models to assess risk of OUD and OD in adults to inform clinical decision making.

Methods

Using PRISMA guidelines [3], we conducted a search of 8 online databases (PubMed, CINAHL, PsycINFO, SocINDEX, Embase, CENTRAL, ACM Digital Libraries, and Xplore) for studies that developed models to predict risk of opioid misuse, abuse, or overdose in adult from inception until July 1, 2020. Abstract screening, full-text review, and data extraction were completed by two independent reviewers in Covidence, with disagreements arbitrated by the senior author. Risk of bias was assessed using the PROBAST [4] tool for predictive model studies.

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It is feasible to develop models to predict risk of opioid use disorder or overdose with high accuracy (AUCs between 0.692 - 0.951)

Scan QR code to view study proposal, search strategy, methodology, & data extraction results.

Table 1: Sample of included articles

Study (Year)	Study design	Outcomes	Data source	Sample Size	Model(s)	Most predictive variables	Accuracy metrics
Reps (2020)	Prospective cohort study	opioid use disorder	1) Optum Clinformatics DataMart 2-4) IBM Databases: Commercial Claims and Encounters (CCAE), Medicare Supplemental and Coordination of Benefits (MDCD), Multi-State Medicaid (MDCR)	1. Optum: 371,704 2. CCAE: 371,258 3. MDCD: 343,552 4. MDCR: 384,424 patients	Logistic regression with LASSO regularization on each database	age 15-29, medical history of substance abuse, mood disorder, anxiety disorder, low back pain, renal impairment, painful neuropathy and recent ER visit (used to develop "Calculator for use of opioid use disorder" (CROUD) score)	Optum: AUC = 0.77 CCAE: AUC = 0.79 MDCD: AUC = 0.85 MDCR: AUC = 0.76 CROUD AUC: 0.72 - 0.83
Sun (2020)	Retrospective cohort study	opioid overdose	Clinformatics Data Mart (Optum)	5,293,880 patients	1. Logistic regression (baseline variables) 2. Logistic regression (top 10 predictors) 3. Logistic regression (baseline variables) 4. Elastic net 5. Random forest	age, gender, region, back and neck pain, opioid dependence, psychosis, depression, anxiety disorder, number of prescriptions for non-opioids, and neuropathic pain	1. AUC: 0.81 2. AUC: 0.83 3. AUC: 0.88 4. AUC: 0.89 5. AUC: 0.86
Workman (2019)	Retrospective cohort study	opioid use disorder	Veterans Affairs Informatics and Computing Infrastructure (VINCI)	45,326 patients, 193,568 outpatient visits	1. Deep learning model (Python packages) 2. Deep learning model (baseline variables) 3. Logistic regression	1. respiratory provider, behavioral health / social services provider, ethnicity (declined), mental health diagnosis, traumatic brain injury 2. mental health diagnosis, traumatic brain injury, behavioral health and social service provider, hydromorphone, respiratory provider 3. respiratory provider, behavioral health / social services provider, mental health diagnosis, pain diagnosis, traumatic brain injury	1. AUC: 0.87 2. AUC: 0.73 3. AUC: 0.72

Results

Figure 1: PRISMA Flow Diagram

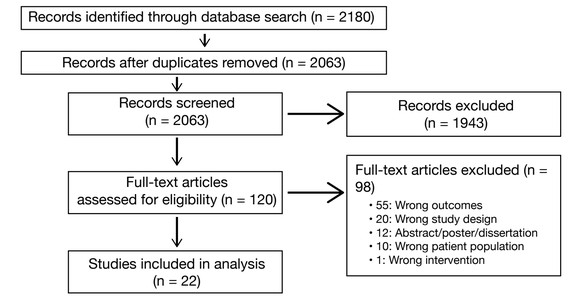

Table 2: Characteristics of included studies (n = 22)

Study types	retrospective cohort (n = 11), prospective cohort (n = 7), observational (n = 3), case-control (n = 1)
Primary outcomes	opioid use disorder (n = 8), opioid overdose (n = 6), persistent opioid use (n = 5), fatal opioid overdose (n = 2), opioid-induced-respiratory depression (n = 1)
Data source	databases (n = 9), electronic health records (n = 7), insurance claims (n = 2), patient-reported data (n = 2), prescription drug monitoring programs (n = 1), multiple sources (n = 1)
Sample size	Range: 762 patients – 5,293,880 patients
Accuracy metrics	AUC or c-statistic (n = 16), Akaike information criterion (n = 1), Euclidean loss (n = 1), aOR (n = 1), sensitivity/specificity (n = 3)
Models	logistic regression (n = 9), multiple models (n = 6), random forest (n = 1), LASSO regression (n = 2), neural network (n = 1), Poisson (n = 1), proportional hazards (n = 1), support vector machine (n = 1).
Most common predictors	age (n = 12), history of mental illness (n = 12), sex or gender (n= 8), history of substance use disorder (n = 8), opioid prescription history (n = 8)

Conclusions & Future Directions

- Stratify findings by model type and evaluate the most predictive input variables
- Many models examine associations but are not predictive; few models are implemented as real-time clinical decision support tools

References

1. Florence CS, Zhou C, Luo F, Xu L. The Economic Burden of Prescription Opioid Overdose, Abuse, and Dependence in the United States, 2013. Med Care. 2016;54(10):901-906.
2. Mattson CL TL, Quinn K, Kariisa M, Patel P, Davis NL. Trends and Geographic Patterns in Drug and Synthetic Opioid Overdose Deaths — United States, 2013–2019. MMWR Morb Mortal Wkly Rep 2021;70:202-207.
3. Page MJ, McKenzie JE, Bossuyt PM, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ. 2021;372:n71.
4. PROBAST: A Tool to Assess the Risk of Bias and Applicability of Prediction Model Studies. Annals of Internal Medicine. 2019;170(1):51-58.