Pain Medicine, 2025, **00**, 1–15
https://doi.org/10.1093/pm/pnaf116
Advance access publication 25 August 2025
Review Article

Evidence-based framework for identifying opioid use disorder in administrative data: A systematic review and methodological development study

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Abstract

Objective: To systematically evaluate existing approaches for identifying opioid use disorder (OUD) in administrative data sets and develop evidence-based recommendations for standardized identification methods.

Design: Systematic review following Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) Scoping Review guidelines with comprehensive literature search and evidence synthesis for framework development.

Setting: Administrative data sets including commercial claims, Medicaid, Medicare, and electronic health records.

Subjects: In brief, 169 studies using administrative codes to identify OUD, primarily from US healthcare systems (94.7%).

Methods: Systematic search of EMBASE, MEDLINE, Google Scholar, and PubMed through February 2024. Three independent reviewers screened articles and extracted data using standardized tools. Study quality was assessed using modified Newcastle-Ottawa Scale. Framework development employed systematic integration of evidence-based components from high-quality studies.

Results: Our analysis of 169 studies revealed four distinct identification approaches: Direct diagnosis codes (36.7%), composite definitions (48.0%), overdose codes (10.1%), and medication-assisted treatment codes (1.2%). Commercial claims data predominated (60.4%), followed by Medicaid claims (10.1%) and electronic health records (7.7%). Multi-modal strategies incorporating both diagnostic and treatment codes showing superior theoretical foundation compared to single-method approaches. Substantial variation existed in reference periods, code requirements, and treatment verification approaches.

Conclusions: An evidence-based framework incorporating diagnosis codes, specific temporal requirements, validated indirect indicators, and treatment evidence provides theoretical foundation for standardized OUD identification protocols. The framework addresses known sources of misclassification while maintaining diagnostic specificity through clinical diagnostic alignment and systematic validation research programs.

Registration: Prospero (CRD42023406173) and OSF (osf.io/ru4j3)

Keywords: opioid use disorder; administrative data; diagnostic coding; ICD-10; systematic review; health services research.

Introduction

Accurate identification of opioid use disorder (OUD) in administrative data sets is fundamental for advancing both substance use disorder research and patient care quality. Valid OUD case definitions enable researchers to leverage large-scale data effectively, particularly for studying rare outcomes, evaluating quality metrics, and conducting comparative effectiveness research. Drug overdose remains the leading cause of death for US residents aged 23 to 46 years, with over 81 000 opioid-involved overdose deaths reported in 2022, more than six times the number in 2002.[1] Many of these individuals had untreated or undertreated OUD,

Received: 10 June 2025. **Revised:** 28 July 2025. **Accepted:** 15 August 2025

highlighting the critical importance of accurate case identification for both research and clinical intervention.[2]

Current approaches to OUD identification in administrative data face multiple intersecting challenges that compromise research validity and clinical utility. Healthcare systems employ diverse coding architectures including International Classification of Diseases, 9th and 10th editions (ICD-9/10) diagnostic codes, Healthcare Common Procedure Coding System (HCPCS) procedure codes, and National Drug Codes (NDC), with implementation varying considerably across different healthcare settings.[3] The transition from ICD-9 to ICD-10 coding systems introduced additional complexity, with research demonstrating significant shifts in identification patterns for OUD.[4,5] Current practice lacks systematic theoretical foundation, relying instead on ad hoc adaptations while facing ongoing challenges in accurately distinguishing OUD from other opioid-related conditions.[6] The Centers for Medicare & Medicaid Services (CMS) Chronic Conditions Warehouse (CCW) represents the standard approach for OUD identification, though validation studies show sensitivity ranging from 84.2% in Medicaid claims to substantially lower rates in other settings, with diagnostic codes sometimes inappropriately applied to justify insurance coverage rather than reflect clinical diagnoses.[3,7,8]

Standardized identification frameworks represent a critical methodological advancement for health services research, addressing current gaps by integrating evidence across diverse administrative data environments. Most research has employed single-system coding approaches, while few studies integrate composite coding architectures to capture the complete spectrum of OUD diagnosis, treatment, and healthcare utilization.[9] Key unresolved implementation challenges include determining appropriate reference periods, code frequency thresholds, exclusion criteria, and methods for coding system integration.[6]

This systematic review evaluates existing approaches for identifying OUD in administrative datasets, synthesizes implementation characteristics across methods, and develops an evidence-based framework for standardized identification. Our framework development approach provides theoretical foundation for subsequent empirical validation while establishing methodological standards for administrative data research. The resulting framework integrates multiple coding systems while maintaining clinical relevance and practical utility for diverse research applications.

Methods

We followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses—Scoping Review (PRISMA-ScR) guidelines and PRISMA Statement for Reporting Literature Searches in Systematic Reviews (PRISMA-S) (Appendix S1,2, and Figure S1 in the Supplementary Files).[10,11] The protocol was a priori registered with PROSPERO (CRD42023406173) and OSF (osf.io/ru4j3).[12] All review procedures were managed using Covidence systematic review software.[13]

We implemented a systematic search strategy across four major bibliographic databases (EMBASE, MEDLINE, Google Scholar, and PubMed) from database inception through February 2024. The search framework centered on 3 key domains: Opioid use (eg, misuse, abuse, dependence, disorder) terminology, medical coding systems, and sourcing of administrative datasets. Database-specific controlled vocabularies, including Medical Subject Headings (MeSH) terms, were employed alongside explicit search terms for common administrative data sources (MarketScan, Optum, Medicare, Medicaid). Gray literature was identified through Google and MedRxiv searches, supplemented by manual reference list review of included articles. A medical research librarian reviewed and verified our search strategy prior to implementation. Complete search specifications are provided in Appendix S3.[14]

Study selection and eligibility criteria

We included peer-reviewed studies published in English (or with available translations) that used administrative codes to identify concepts related to disordered opioid use, including both prescription and illicit opioid use. Studies were excluded if they used non-coding phenotypes, or solely natural language processing. Conference abstracts, letters, commentaries, and editorials were excluded.

We differentiated between studies identifying OUD directly versus those identifying other opioid-related conditions based on: Explicit statements by authors regarding their intent to identify OUD; alignment of coding approaches with diagnostic criteria for OUD; and use of clinical terminology that indicates patterns consistent with an OUD diagnosis without explicitly using the term "OUD" itself such as documented "chronic use of illicit opioids" or "non-medical use of prescription opioids" in the medical record. Studies that documented overdose or poisoning events without establishing a causal relationship to patterns of opioid use meeting clinical criteria for OUD, or without explicit OUD diagnosis documentation, were categorized separately to maintain clinical and phenomenological distinction.

Screening process

Study screening and selection occurred through a multi-stage process using Covidence systematic review software.[13] Retrieved articles were imported into Covidence, and duplicate records were systematically removed using the platform's deduplication functionality. Initial screening of titles and abstracts was performed independently by 3 reviewers (R.W.H., K.B., M.C.B,A.) to evaluate eligibility based on the presence of algorithms utilizing standardized coding systems (ICD, Current Procedural Terminology [CPT], Healthcare Common Procedure Coding System [HCPCS], or National Drug Code [NDC]) for identifying opioid use disorder (OUD), opioid misuse, abuse, dependence, or remission in electronic health records or administrative databases.

Studies were included if they constituted original peer-reviewed research published in English (or translated to English) prior to February 2024, contained specific algorithms using administrative codes to identify disordered opioid use in claims databases or electronic health records, and addressed prescription and/or illicit opioid use. Exclusion criteria encompassed OUD phenotypes based on non-administrative criteria (such as natural language processing of free-text notes), studies of opioid poisoning without established relationship to OUD, conference proceedings without full-text articles, and editorial content.

Following initial screening, 4 reviewers (R.W.H., K.B., M.C., M.C.B.A.) evaluated potentially eligible articles, with full-text versions independently assessed by 3 reviewers (R.W,H., K,B., M.C.) using the predetermined criteria.

A dedicated resolution team (R.W.H., K.T.B., M.C., M.C.B.A., E.H., D.G.) adjudicated disagreements, with final decisions determined by consensus.

Data extraction

Data were recorded using a comprehensive tool developed within Covidence, with extraction performed by trained reviewers using standardized forms. All extraction was performed through manual reviewer assessment following established Cochrane review guidelines[13] rather than automated processes. Geographic location was determined by data source origin, irrespective of researcher affiliations. Primary study objectives were extracted from structured abstract sections labeled "Objective" or "Purpose"; in their absence, we identified statements containing terms such as "aim," "purpose," or "objective" within the abstract or introduction.

Studies were classified predominantly as observational, with additional categories for descriptive and surveillance studies according to predetermined design categorization guidelines. Study scope was determined by the most restrictive data source when multiple sources were used. Settings were categorized using standardized terminology (Inpatient, Outpatient, Emergency Department), with unique settings documented as encountered. Age range determination relied on explicit methodology statements or age-stratified results tables, with assumptions made for specific populations (eg, Medicare beneficiaries assumed to be older adults). Data timeframes encompassed the complete analytical period, including pre- and post-study intervals.

The authors' primary clinical focus was determined from the title, objective, abstract emphasis and article methods section. Drug type categorization captured both specific medications and associated codes, though most studies did not restrict populations by drug type due to diagnostic code limitations in distinguishing between legal and illegal drug use. Code definitions were standardized by converting range notations to individual codes through reference to official ICD documentation.[15] While primary definitions were based on explicit diagnostic codes (ICD, CPT, HCPCS, or NDC), with additional contextual restrictions captured narratively. Studies using exclusively narrative definitions were excluded.

Key findings were extracted from structured abstract, results, discussion sections, or conclusions. When multiple OUD definitions were compared, sensitivity and specificity statistics were included when reported. Coding limitations and recommendations were extracted from methodology sections describing code usage or relevant discussion sections addressing coding-related limitations. Additional references meeting inclusion criteria were identified through citation screening and systematic reviews. Duplicate articles were resolved by retaining the earliest publication while excluding subsequent versions. Notable methodological variations, such as country-specific coding systems, were documented to provide context for interpretation. At least 2 of 5 reviewers independently extracted data, with discrepancies resolved through consensus discussion of the resolution team.

Study quality

Study quality was evaluated using a modified Newcastle-Ottawa Scale (mNOS), adapted for assessing administrative data studies.[16–18] The mNOS used a 9-star maximum rating across 3 domains: Selection (4 stars): Evaluating cohort representativeness and exposure ascertainment, with particular attention to how clearly studies defined OUD versus related conditions. Comparability (2 stars): Examining demographic and subpopulation controls, including assessment of whether studies appropriately distinguished between prescription opioid use, illicit use, and polysubstance involvement. Outcome (3 stars): Assessing outcome definitions, follow-up, and coding reliability, including whether studies employed validation against clinical standards when available. Additional quality assessment elements specific to administrative data studies included evaluation of code selection appropriateness, documentation of coding system transitions, and assessment of whether studies appropriately accounted for healthcare system factors affecting coding practices.

Data analysis

We conducted a comprehensive analysis to evaluate opioid use disorder (OUD) identification methodologies in administrative data. Studies were systematically categorized according to population characteristics (age groups, inclusion/exclusion criteria), data source types (commercial claims, Medicare/Medicaid, health system Electronic Health Records [her]), and coding frameworks (ICD-9, ICD-10, CPT, HCPCS, NDC). Specific diagnostic, procedural, and pharmaceutical codes used for OUD identification were extracted from each study. Algorithm components were systematically deconstructed to identify core elements, including diagnostic criteria, medication patterns, healthcare utilization markers, and exclusion parameters. Assessment of how studies addressed potential misclassification through validation techniques was performed. Statistical approaches for algorithm evaluation were recorded when available, including sensitivity, specificity, positive predictive values, and negative predictive values compared against reference standards. All analyses were conducted using STATA v.17 (StataCorp LLC).[19]

Framework development methodology

Framework development followed established methodological standards for evidence-based theoretical construction.[20] Component selection required systematic evidence support from multiple high-quality studies based on modified Newcastle-Ottawa Scale assessment. Framework architecture integrated diagnostic specificity requirements with practical implementation considerations across diverse administrative data environments. Stakeholder perspectives were incorporated through systematic analysis of researcher-reported limitations and recommendations across included studies. The development process prioritized clinical alignment with DSM-5 criteria[21] while addressing implementation challenges identified through systematic review synthesis.

Framework component justification employed content validity approaches requiring convergent evidence across multiple studies for inclusion. Exclusion criteria addressed systematic sources of misclassification documented in validation research. Temporal requirements aligned with established diagnostic timeframes while accommodating diverse research applications. The systematic integration process ensured theoretical coherence while maintaining practical utility for administrative data research.

OUD identification in administrative code framework development

Development of our evidence-based OUD identification framework employed systematic methodology. Common approaches and selected identification codesets were identified across high-quality studies (mNOS >7), followed by analysis of validation study findings to determine approaches with superior sensitivity/specificity (where available). Selection of ICD-10[15] diagnostic codes was performed to align with the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition–revised (DSM-5) criteria[21] for mild and moderate/severe OUD. Only codes that corresponded to the clinical parameters for OUD diagnosis as defined in DSM-5 were incorporated (eg, opioid abuse (F11.1) corresponding to mild OUD and opioid dependence (F11.2) corresponding to moderate/severe OUD[22]) while codes representing potentially related but clinically distinct conditions (eg, opioid use [F11.9] corresponding to opioid misuse[23] and long-term [current] use of opiate analgesic [Z79.891]) were excluded from the identification algorithm. This approach ensured diagnostic specificity and reduced potential misclassification of non-OUD opioid-related conditions. Selection of NDC was performed to align with the Food and Drug Administration (FDA) labeled medication indication. Only NDCs for medications with an indication for Medications for Opioid Use Disorder (MOUD) were included. When the indication could not be determined by NDC (eg, methadone), differentiation was based on the context of use (opioid treatment program [eg, place of service code 58] vs general medical setting) and procedure codes (eg, H0020, G2067, G2078, etc.). Identification of places of service (POS) was performed to reduce the likelihood of false positive OUD diagnosis in environments that are not associated with clinical diagnostic decision making or influenced by known non-medical factors such as insurance requirements (eg, laboratory services, POS 81).[3,24]

Implementation feasibility across different administrative data environments was evaluated, involving an examination of time frames used to assess the presence of an OUD indicator (eg, 1-year vs 2-years). The proposed framework was then compared to the CMS Chronic Conditions Warehouse methodology,[7] with modifications based on identified limitations in current approaches.

Results

Our comprehensive literature search across all databases identified 9561 potentially relevant works published between January 2000 and February 2024, including 5106 from traditional literature databases (eg, Medline, PubMed, Google Scholar, and Embase) and 4385 from grey literature sources (eg, MedRxiv and full text conference proceedings) (Figure S1). Manual reference list searching identified an additional 70 works.[25]After removing duplicates and applying final inclusion/exclusion criteria, 169 studies met all requirements for analysis.

Study quality assessment and characteristics

Quality assessment of the 169 identified studies[3,4,8,26–191] (Appendix S4) using the mNOS16-18 revealed consistently robust methodological approaches across studies (Appendix S5). In the Selection domain, studies averaged 2.29 out of 4 possible points, reflecting some variability in cohort selection methods and exposure ascertainment. The Comparability domain showed moderate strength with an average score of 1.42 out of 2 possible points. Studies achieving the maximum comparability score distinguished themselves through comprehensive adjustment for demographic confounders and special consideration of clinically relevant subpopulations, such as pregnancy and pediatric cases. The outcome domain emerged as the strongest methodological component, with 82% of studies achieving the maximum 3 points, reflecting clear documentation of outcome measures, appropriate follow-up duration, and adequate tracking of cases throughout study periods. Seventy studies were considered high quality (Appendix S5).

Most studies were conducted in the USA (160/169, 94.7%), with commercial claims data predominating (102/169, 60.4%), followed by Medicaid claims (17/169, 10.1%) and electronic health records (13/169, 7.7%), while Medicare claims comprised only 4.1% (7/169). Study settings commonly included multiple sites combining inpatient, outpatient, and emergency departments (49/169, 29.0%), followed by inpatient-only settings (33/169, 19.5%). The majority were observational studies (162/169, 95.9%) with national scope (92/169, 54.4%), and most publications occurred between 2019–2022 (98/169, 58.0%). Approximately 29.0% of studies focused on state-level analyses (Table 1).

Among 169 studies, the majority included adult populations: Adult/older adult (57/169, 33.7%), adolescent/adult/older adult (42/169, 24.9%), and adolescent/adult (38/169, 22.5%). Regarding opioid classifications, unspecified opioids predominated (109/169, 64.5%), followed by prescription opioids (31/169, 18.3%), and combined prescription-illicit use (27/169, 16.0%). Among specific agents, methadone was most frequently studied (20/169, 11.8%), followed by buprenorphine (16/169, 9.5%), with heroin being the most investigated illicit opioid (18/169, 10.9%) (Table 2).

Evidence synthesis for framework development

Predominant coding methodologies were ICD systems, with ICD-9 representing 43.8% (74/169) of studies, followed by ICD-10 (36/169, 21.3%). Multiple coding sources were employed in 33.8% (57/169) of studies, most frequently combining ICD-9 and ICD-10 (46/169, 27.2%). Healthcare Common Procedure Coding System and NDC were infrequently used in isolation (1/169, 0.6% each) (Table S1).

Analysis revealed four fundamental approaches requiring systematic integration: Direct diagnostic identification through ICD codes, proxy identification via overdose indicators, indirect identification through treatment engagement, and composite multi-modal strategies. Each approach demonstrated distinct strengths and limitations requiring theoretical reconciliation through evidence-based framework development.

Framework component identification

Opioid use disorder (OUD) identification approaches varied across studies and were categorized into 5 distinct methodologies. (1) Direct identification using ICD diagnosis codes alone was employed in 36.7% (62/169) of studies. (2) Proxy measures identification (using ICD overdose/poisoning codes) were used in 10.1% (17/169) of studies. (3) Indirect identification (using NDC/HCPCS codes for MOUD) was rare at 1.2% (2/169). (4) Combination approaches (direct, proxy,

Table 1. Summary characteristics of studies defining opioid use disorder.

Study population		Number of studies (n)	Percentage of total (%)
Country			
	USA	160	94.7
	Germany	2	1.2
	Other[a]	7	4.1
Data source[b]			
	Commercial claims (CC)	102	60.4
	Electronic health records (EHR)	13	7.7
	Medicare claims (Medicare)	7	4.1
	Medicaid claims (Medicaid)	17	10.1
	Veterans' Health Administration (VA) claims	5	3.0
	German Statutory Health Insurance claims	2	1.2
	Multiple sources: CC, Medicaid	3	1.8
	Multiple sources: CC, Medicare	1	0.6
	Multiple sources: CC, EHR	2	1.2
	Multiple sources: CC, Vital statistics	2	1.2
	Multiple sources: CC, other	1	0.6
	Multiple sources: Medicaid, EHR	1	0.6
	Multiple sources: Medicaid, Vital statistics	1	0.6
	Multiple sources: Medicaid, Vital statistics, other	1	0.6
	Multiple sources: Medicare, Vital statistics	1	0.6
	Multiple sources: Medicaid, other	3	1.8
	Other[c]	7	4.1
Study setting			
	Inpatient (IP)	33	19.5
	Outpatient (OP)	11	6.5
	Emergency department (ED)	10	6.0
	Morgue, Medical Examiner (ME)	3	1.8
	Multiple sites: IP, OP, ED, PH	5	3.0
	Multiple sites: IP, OP, ED, other[d]	4	2.4
	Multiple sites: IP, OP, ED	49	29.0
	Multiple sites: IP, OP, ED, Long-Term Care (LT)	2	1.2
	Multiple sites: IP, OP, PH	2	1.2
	Multiple sites: IP, OP, other[d]	3	1.8
	Multiple sites: IP, OP	33	19.5
	Multiple sites: IP, PH	1	0.6
	Multiple sites: IP, ED	9	5.3
	Multiple sites: OP, ED	1	0.6
	Multiple sites: ME, PH	2	1.2
	Other[d]	1	0.6
Study design			
	Observational	162	95.9
	Model building and training	5	3.0
	Descriptive	2	1.2
Study scope			
	National	92	54.4
	National: Non-US	7	4.1
	State or Multiple states	49	29.0
	Region (Multiple communities)	2	1.2
	Region: Non-US	1	0.6
	Community	4	2.4
	Health system	10	5.9
	Hospital	3	1.8
	Hospital: Non-US	1	0.6
Publication Year			
	2023	7	4.1
	2022	25	14.8
	2021	24	14.2
	2020	31	18.3
	2019	18	10.7
	2018	15	8.9
	2017	12	7.1
	2016	4	2.4
	2015	5	3.0
	2014	11	6.5
	2013	6	3.6
	2012 and earlier	11	6.5

[a] Other countries include Australia, Columbia, Czech Republic, England, and South Africa, each with a single manuscript.
[b] For full list of data sources, please see eAppendix 3 in Supplementary material.
[c] Other data sources include NCHS Multiple Cause of Death Research files, NHAMCS, National Hospital and Ambulatory Medical Care Survey; PDMP, Maryland Prescription drug monitoring program; All-payer hospital discharge claims; OCME, Office of the Chief Medical Examiner records; TN Death Certificates; CSMD, TN Controlled Substance Monitoring Database; AHEDD, New Hampshire Department of Health and Human Services Automated Hospital Emergency Department Data; MDPH, Massachusetts Department of Public Health; Hospital Administrative Data, Registry of Vital Statistics; EMS, Emergency Medical Services; PDMP, Kentucky's Prescription Drug Monitoring Program; Kentucky Medicaid each with a single manuscript.
[d] Other study settings include residential treatment, behavioral health centers, personal residence, Skilled Nursing Facilities (SNF) alone or in combination with each other or the other sites listed.

and/or indirect) were the most common at 52.1% (88/169), with direct diagnosis and proxy methods representing the most common combination approach at 42.6% (72/169) (Table 3).

Primary study aims focused predominantly on opioid use disorder (OUD) investigations, with 26.0% (44/169) examining OUD alone and 26.6% (42/169) studying OUD with additional factors. Studies specifically focused on opioid abuse comprised 19.0% (32/169), while opioid overdose/poisoning investigations represented 10.7% (18/169). Opioid dependence studies accounted for 10.1% (17/169), and MOUD analyses were least common (2/169, 1.2%) (Table S2).

Direct definition approaches

For direct definitions of OUD using ICD9 codes, 304.01 (opioid type dependence, continuous) and 304.02 (opioid type dependence, episodic) were the most frequently used, appearing in 89.2% (116/130) of papers with ICD-9 coding systems. This was followed by 304.00 (opioid type dependence, unspecified) at 86.9% (113/130) and 305.52 (opioid abuse, episodic) at 80.8% (105/130).

Among ICD-10 codes analyzed, F11.20 (opioid dependence, uncomplicated) was most frequently observed, appearing in

Table 2. Population characteristics of study population defining opioid use disorder.

Study population	Number of studies (n)	Percentage of total (%)
Age range (years)		
65 and older (older adult)	3	1.8
18–65 (adult)	26	15.4
10–18 (adolescent)	3	1.8
Adolescent, adult, older adult	42	24.9
Adolescent, adult	38	22.5
Adult, older adult	57	33.7
All opioids		
Opioid—not otherwise specified (NOS)	109	64.5
Opioid—prescription	31	18.3
Opioid—illicit (non-prescription)	2	1.2
Opioid—prescription, illicit	27	16.0
Illicit opioids		
Heroin	18	10.9
Carfentanil	1	0.6
Fentanyl (non-prescription)	1	0.6
Prescriptions, opioids		
Buprenex (IV Buprenorphine)	1	0.6
Buprenorphine	16	9.5
Buprenorphine-Naloxone	3	1.8
Butorphanol	4	2.4
Butrans	1	0.6
Codeine	10	5.9
Dihydrocodeine	6	3.6
Fentanyl	9	5.3
Hydrocodone	8	4.7
Hydromorphone	9	5.3
Levorphanol	5	3
Meperidine	8	4.7
Methadone	20	11.8
Morphine	11	6.5
Nalbuphine	1	0.6
Naloxone	1	0.6
Naltrexone	8	4.7
Opium	5	3
Oxycodone	10	5.9
Oxymorphone	6	3.6
Pentazocine	5	3
Tapentadol	9	5.3
Tramadol	9	5.3

Demographic and substance-specific characteristics of study populations. Age ranges are categorized into major life stages. Opioid types are classified as general categories (all opioids), illicit opioids, and prescription opioids, with detailed breakdown of specific prescription medications studied.

85.6% (77/90) of studies using ICD-10 codes to define OUD. This was followed by F11.23 (opioid dependence with withdrawal) and F11.24 (opioid dependence with opioid-induced mood disorder), each appearing in 83.33% (75/90). Codes related to opioid "abuse" (F11.10) appeared in 82.2% (74/90) of papers with ICD-10 coding systems. Notably, codes for opioid dependence in remission (F11.21) were included in only 55.6% (50/90) of these studies, indicating a potential gap in capturing the full spectrum of OUD states.

Proxy definition approaches

In the analysis of proxy definitions for OUD using opioid poisoning and overdose codes in ICD-9, the code 965.02 (poisoning by methadone) was identified in 55.4% (72/130) of studies. The codes 965.00 (poisoning by opium, unspecified) and 965.09 (poisoning by other opiates and related narcotics) were observed with similar frequency, each appearing in 54.6% (71/130) of studies employing ICD-9 based OUD proxy definitions.

Table 3. Coding definitions of Opioid Use Disorder (OUD).

Definition	Number of studies (n)	Percentage of total (%)
Direct[a]	62	36.7
Proxy (overdose)[b]	17	10.1
Indirect (MAT/MOUD)[c]	2	1.2
Direct + proxy (overdose)	72	42.6
Direct + indirect (MOUD/MAT)	3	1.8
Direct + proxy (overdose) + indirect (MOUD/MAT)	6	3.6

[a] Direct identification refers to the use of ICD diagnostic codes that explicitly correspond to DSM-5 criteria for OUD (F11.1x for mild OUD/opioid abuse and F11.2x for moderate-severe OUD/opioid dependence). This approach identifies OUD as the primary clinical condition rather than using proxy indicators such as overdose events or treatment engagement patterns.
[b] Proxy = overdose/poisoning codes used as indicators of potential OUD.
[c] Indirect = MOUD prescription or procedure codes indicating OUD treatment.

The proxy definition of OUD in studies using ICD-10 was most frequently comprised of poisoning codes T40.0X1A (poisoning by opium, accidental, initial encounter), T40.1X1A (poisoning by heroin, accidental, initial encounter), and T40.2X1A (poisoning by other opioids, accidental, initial), each appearing in 45.6% (41/90) of papers. T40.3X1A (poisoning by methadone, accidental, initial) appeared in 44.4% (40/90) of studies.

Indirect definition approaches

An indirect definition of OUD based solely on MOUD prescription was used in only one study and was limited to NDCs of buprenorphine formulations for MOUD.[122] More commonly, MOUD-based identification was used as part of a composite approach alongside diagnostic codes. The specific NDCs and HCPCS codes used for MOUD identification varied widely across studies, with little standardization in approach.

Code combinations and patterns

The analysis of code combinations revealed frequent intersections between opioid dependence and abuse diagnoses with poisoning-related events, and rarely intersections with drug codes. The 2 most common ICD-9 combinations were 304.00 (opioid-type dependence) with 965.00 (poisoning by opium) and 304.01 (opioid type dependence, continuous) with 965.02 (poisoning by methadone), representing 17.5% (62/130) of all ICD-9 combinations. The pairing of 305.50 (non-dependent opioid abuse) with 965.09 (poisoning by other opiates and related narcotics) was the second most common, with 63.3% (57/90) of the papers containing the combination.

In studies using ICD-10 coding systems, the most frequent code combination was F11.20 (opioid dependence) with T40.0X1A (poisoning by opium, accidental), representing 36.7% (33/90) of observed combinations. This highlights the interplay between chronic opioid dependency and acute poisoning events. The pairing of F11.10 (opioid abuse) with T40.3X1A (poisoning by methadone, accidental) accounted for 35.6% (32/90), indicating the ongoing risk of poisoning among individuals with a history of abuse. The combination of opioid abuse (F11.10) with methadone maintenance

Table 4. Comparison between Centers for Medicare & Medicaid Services (CMS) Chronic Conditions Warehouse (CCW) and Wake Forest Opioid Use Disorder (OUD) definitions.

Criteria	WF OUD definition	CMS OUD definition
Code types		
Direct Diagnostic Codes	F11.1x, F11.2x codes (valid clinical settings only)	Broader set of ICD codes including non-clinical settings
Opioid Poisoning Codes	Selected overdose/poisoning codes (T40.x series)	All overdose-related ED visits and hospitalizations
MOUD Codes	Buprenorphine NDCs and methadone in OTP setting only	Multiple MOUD codes without context restrictions
Identification criteria		
Reference period	≥2 qualifying codes within 12 months (can extend to 24 months)	≥1 inpatient OR ≥2 outpatient claims within 24 months
Settings	Excludes codes from lab and DME settings	No settings exclusions
Remission status	Distinguishes active OUD from remission	No distinction between active OUD and remission

Reference period aligns with DSM-5 diagnostic criteria requiring persistent symptoms over 12-month periods, with 24-month option for CCW-compatible analyses and coverage continuity considerations.
Naltrexone (oral and injectable) with appropriate clinical context verification.
This table compares the methodological approaches for identifying opioid use disorder in administrative data between the Wake Forest definition and the Centers for Medicare & Medicaid Services Chronic Conditions Warehouse definition. The comparison highlights key differences in diagnostic code selection, identification criteria, and implementation parameters. The WF definition employs a more targeted approach with specific F11.1x and F11.2x diagnostic codes from clinical settings only, selected overdose/poisoning codes, and context-specific medication for OUD codes. It requires at least 2 qualifying codes within a 12-month period (with flexibility to extend to 24 months), excludes codes from laboratory and durable medical equipment settings, and distinguishes between active OUD and remission states. In contrast, the CMS definition uses a broader set of ICD codes including those from non-clinical settings, incorporates all overdose-related emergency department visits and hospitalizations, includes multiple medication codes without context restrictions, requires at least one inpatient or two outpatient claims within 24 months, does not exclude any settings, and makes no distinction between active OUD and remission states.

treatment (HCPCS H0020, frequently mischaracterized as "behavioral health counseling" in several studies) was identified in 5.6% (5/90) of analyses, indicating the incorporation of methadone maintenance therapeutic interventions within the management of patients diagnosed with opioid abuse. Finally, T40.0X1A (poisoning by opium, initial encounter) combined with T40.2X4A (poisoning by other synthetic narcotics, subsequent encounter) was observed in 42.2% (38/90) of combinations, indicating the poly-substance nature of opioid poisoning in recent clinical data (Appendix S4).

Evidence-Based framework architecture

The Wake Forest Framework represents systematic integration of evidence-based components addressing identified limitations in current approaches. Component selection followed systematic criteria including diagnostic specificity alignment with DSM-5,[21] evidence quality assessment based on mNOS scores, practical implementation feasibility across administrative data environments, and error reduction potential documented in validation studies.

Framework architecture distinguishes between active OUD identification and remission states, incorporates treatment engagement indicators through verified MOUD codes, and excludes non-clinical coding contexts known to generate false positives (Table 4). This theoretical structure enables precise case identification while maintaining sensitivity for clinical research applications across diverse healthcare settings.

Through systematic evidence synthesis, we developed a standardized multi-modal identification framework that integrates key components from successful strategies identified in high-quality studies (mNOS greater than 7). The framework employs ICD diagnostic codes aligning with DSM-5 criteria,[21] HCPCS procedure codes indicating treatment engagement, validated poisoning and overdose indicators, and prescription claims for MOUD. Framework implementation employs a 12-month reference period consistent with DSM-5 diagnostic timeframes, with optional 24-month extension for CCW-aligned analyses and excludes claims from non-clinical settings known to generate false positives.

Code F11.90 (opioid use, unspecified) was intentionally excluded from our framework development due to its lack of specificity for OUD diagnosis (per WHO ICD definitions).[15] This code is frequently applied to patients receiving prescribed long-acting opioids for legitimate medical purposes who misuse the medications and does not align with DSM-5 criteria for OUD.[23] Our framework restricts inclusion to F11.1x (opioid abuse) and F11.2x (opioid dependence) codes that correspond to mild and moderate/severe OUD classifications respectively, ensuring diagnostic specificity while reducing misclassification of opioid misuse.

Oral naltrexone presents unique considerations as it is FDA-approved for "the blockade of the effects of exogenously administered opioids" and alcohol use disorder.[192] When oral naltrexone codes appear with concurrent OUD diagnostic codes, this represents valid evidence of OUD treatment engagement. However, when naltrexone appears with alcohol use disorder codes but without direct OUD identification, we recommend excluding these cases from OUD identification to avoid misclassification. Injectable naltrexone (Vivitrol) has more specific OUD indication and can be included with appropriate clinical context verification.

Analysis of OUD definitions revealed significant structural differences between the CMS-CCW algorithm and the reviewed established literature. Therefore, the updated Wake Forest (WF) definition proposed here aligned with the literature and included 4 identification pathways: Direct identification via ICD-10 diagnostic codes, proxy identification through opioid poisoning and overdose codes, indirect identification using MOUD codes and a combination of the 3 identification pathways. Both CCW and the updated definition required at least two qualifying codes within the reference period, with the updated algorithm applying a 12-month timeframe (consistent with DSM-5 criteria), while maintaining the option for a 2-year timeframe to enable CCW-aligned analyses. The updated definition implemented additional exclusion parameters by removing diagnosis codes from non-clinical settings (laboratory services) and durable medical equipment claims. Clinical context was incorporated by excluding naltrexone-associated codes when concurrent

Alcohol Use Disorder codes were present without direct OUD identification, addressing potential substance use disorder misclassification seen in the CCW definition. The complete Wake Forest Framework implementation algorithm is detailed in Appendix S6 and Figure S2, providing step-by-step guidance for researchers seeking to apply this standardized approach in their administrative data analyses. This comprehensive approach aims to optimize identification of OUD cases within administrative datasets, while maintaining alignment with current diagnostic criteria and coding standards. Unlike the CCW approach, the updated definition framework distinguishes between active OUD and remission states, explicitly incorporates treatment data, and differentiates between diagnostic codes that directly identify OUD vs related conditions that require additional verification.

Discussion

This systematic review represents the first comprehensive evaluation of OUD identification methodologies in administrative data, analyzing 169 studies to develop evidence-based recommendations. The resulting framework addresses critical methodological gaps in current practice while establishing theoretical foundation for standardized protocols across diverse research applications.

The proposed framework offers several theoretical advances over existing approaches. First, systematic integration of multiple identification pathways captures the complete spectrum of OUD cases while maintaining diagnostic specificity through DSM-5 alignment. Second, explicit exclusion criteria address known sources of misclassification identified through systematic review synthesis. Third, temporal requirements align with established diagnostic criteria while accommodating diverse research applications through modular implementation options.

This framework enables multiple research applications including prevalence estimation, treatment effectiveness evaluation, and health services utilization analysis. The modular structure permits adaptation for specific research contexts while maintaining core methodological rigor through systematic component selection. Implementation guidance supports consistent application across diverse administrative data environments, from commercial claims databases to integrated health system electronic health records.

Administrative codes for identifying OUD demonstrate both utility and significant limitations in current clinical practice and research. Validation studies against clinical records have shown variable results, with sensitivity ranging from 84.2% in Medicaid claims data to more modest identification rates.[8] While Chartash et al.[91] achieved high positive and negative predictive values using electronic health record-based algorithms validated against physician review, Lagisetty et al.[3] found only 60% of administratively coded OUD cases had supporting clinical documentation, with accuracy compromised by the inclusion of laboratory claims and reliance on single diagnostic codes. The ICD-9 to ICD-10 transition introduced additional challenges, with studies documenting substantial shifts in identification patterns.[65,175]

Composite methods that integrate multiple identification approaches show promise for comprehensive case capture. Carrell et al.[54] developed a classification algorithm achieving a positive predictive value of 0.572, while Shen et al.[50] found that using NDC codes for buprenorphine prescriptions identified 44% of cases that would have been missed using ICD diagnosis codes alone. Arifkhanova et al.[92] found that expanded definitions incorporating clinical markers identified 136% more unique patients compared to diagnostic codes alone, findings supported by subsequent work.[119]

The appropriate identification approach varies significantly by research context. Treatment engagement studies require different approaches than prevalence estimates or overdose risk assessments. Many research teams successfully tailored their strategies to their specific questions, with treatment studies often excluding MOUD codes to avoid circular reasoning. The distinction between OUD and related conditions, particularly opioid overdose/poisoning, warrants careful consideration, as overdose events may occur without indicating OUD, especially with the increased prevalence of fentanyl contamination in non-opioid substances.[193]

Population-level surveillance studies successfully employed administrative codes to track prevalence trends and geographic patterns, with Thompson et al.[119] documenting county-level OUD prevalence ranging from 1.3% to 17.7%. Setting-specific variations in code performance suggest the need for context-specific validation.[52,70,171] Geographic variation in coding practices potentially reflects differences in state Medicaid policies, regional treatment availability, and local documentation standards.

Temporal analysis of methodological evolution shows an increasing trend toward composite approaches that combine multiple identification methods. Recent advances in machine learning approaches show promise for improving identification accuracy, with Segal et al.[104] achieving a c-statistic of 0.959 for early OUD diagnosis. However, natural language processing approaches are limited by the availability of high-quality medical documentation that is not available in administrative databases including Medicare, Medicaid, and most commercial payers used for large scale analyses.

The CMS-CCW methodology provides a foundational framework but includes codes assigned in non-clinical settings and non-specific codes identified as contributing to false positives.[3] Our analysis revealed that researchers rely primarily on either direct diagnosis codes or combined direct-proxy approaches, with commercial claims data dominating at 60.4% of studies and an increasing trend toward composite approaches.

The primary methodological challenge addressed by this framework involves the misalignment between DSM-5 and ICD-10 diagnostic criteria. While DSM-5 stratifies OUD into mild, moderate, and severe categories, ICD-10 employs a different taxonomic approach with "use," "abuse," and "dependence" categories. The disconnect between diagnostic criteria and coding leads to potential confusion by clinicians applying diagnostic codes to the medical record, resulting in lack of reliability in retrospective assessment of administrative records. Administrative data's inherent temporal limitations complicate differentiation between active disease and remission states, with our analysis finding remission codes appeared in only 55.6% of studies using ICD-10.

Healthcare provider stigma and patient reluctance to disclose substance use due to anticipated stigma represent significant barriers to accurate OUD diagnosis and subsequent coding in administrative data sets. McCurry et al.[194] documented that perceived stigma, along with various barriers and facilitators, significantly impacts clinicians' documentation and healthcare-seeking behavior among individuals with

OUD. This stigma-related underdiagnosis contributes to the sensitivity limitations observed in administrative coding approaches and underscores the importance of composite identification strategies that incorporate multiple evidence sources beyond diagnostic codes alone.

Framework implementation considerations

The modular design of our framework enables adaptation for varying research contexts. For studies requiring high diagnostic certainty (such as comparative effectiveness research or clinical trials), researchers may implement more restrictive criteria requiring multiple diagnostic codes plus treatment evidence. Conversely, epidemiological surveillance studies may benefit from more inclusive approaches that incorporate single MOUD claims when supported by clinical context indicators. The framework components can be weighted differentially based on study objectives, with direct diagnostic codes receiving highest priority for specificity-focused applications, while composite approaches maximize sensitivity for population health assessments.

The 12-month reference period aligns with DSM-5 diagnostic criteria requiring symptom persistence over time. However, we acknowledge that insurance coverage churning, particularly in Medicaid populations, may limit the availability of continuous claims data. For populations with known coverage instability, researchers may need to implement modified approaches such as shorter observation periods when sufficient qualifying codes are present or use probabilistic linkage methods across coverage periods. The framework's modular design permits such adaptations while maintaining core methodological rigor.

Several considerations inform framework application and future development. First, comprehensive empirical validation across diverse healthcare settings will strengthen evidence for optimal implementation approaches and component weighting strategies. Second, natural language processing integration represents promising extension for capturing clinical documentation patterns not reflected in structured coding. Third, international coding system adaptation requires systematic evaluation of framework transferability beyond US administrative data environments. For health systems without comprehensive claims data, the framework adapts through prioritized diagnostic code implementation while incorporating available procedure codes and treatment indicators when available.

Framework modularity enables systematic evaluation of component effectiveness across different administrative data contexts through strict adherence to ICD definitions and DSM-5 timeframes, exclusion of error-prone service locations, requiring multiple qualifying codes, and targeted inclusion of verified treatment and poisoning indicators. This comprehensive approach provides methodological foundation for standardized OUD identification while supporting consistent case identification across research contexts and enabling systematic evaluation of identification strategy effectiveness.

Conclusion

This evidence-based framework addresses existing methodological limitations through systematic integration of validated components while establishing pathways for empirical validation research. Flexible, component-based design enables systematic evaluation of identification strategy effectiveness across different administrative data contexts, supporting evidence-based refinement and adaptation strategies.

Acknowledgements

The authors would like to Claire Herrman-Moran, Catherine Xie, Yiyang Huang, Max Morrow and Suiyue Cui for their assistance with literature extraction. Also, the authors would like to thank Dr Tamara Haegerich for discussions of these concepts.

Supplementary material

Supplementary material is available at *Pain Medicine* online.

Funding

Research reported in this publication was supported by National Institutes of Health (NIH) HEAL Initiative, and National Institute for Drug Abuse under grant numbers U01DA057016, R24DA055306, R24DA058606, and U24DA057612.

Conflicts of interest: R.W.H. —Cooperative (eg, U01) NIH grants as listed, NIH grants not related to this work (UH3AR077360), Nevro, Inc—research funds to the institution topic—painful diabetic neuropathy and not related to this work, and State Farm—expert/consulting not related to this work. K.T.B. —No relevant COI. M.D.C. —No relevant COI. E.L.H. —Cooperative (eg, U01) NIH grant as listed. D.G. —No relevant COI.. M.C.B.A. —Cooperative (eg, U01, U24) NIH grants as listed.

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Pain Medicine, 2025, 00, 1–15
https://doi.org/10.1093/pm/pnaf116
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