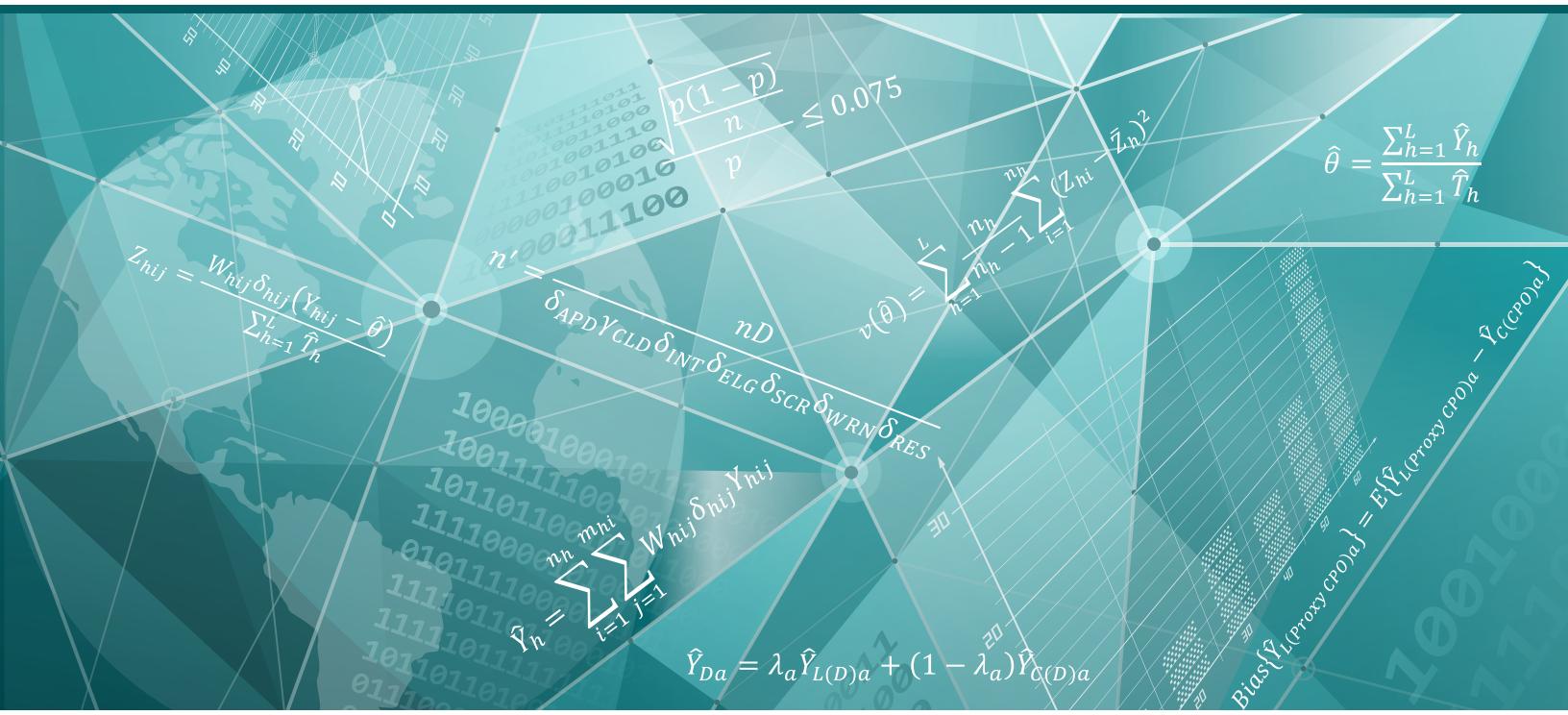
NATIONAL CENTER FOR HEALTH STATISTICS

Vital and Health Statistics

Series 2, Number 205

January 2024



Validation of the Enhanced Opioid Identification and Co-occurring Disorders Algorithms

Data Evaluation and Methods Research

Centers for Disease Control and Prevention
National Center for Health Statistics

NCHS reports can be downloaded from: https://www.cdc.gov/nchs/products/index.htm.

Suggested citation

Brown AM, White DG, Adams NB, Badwe R, Shaikh S, Guluma L. Validation of the enhanced opioid identification and co-occurring disorders algorithms. National Center for Health Statistics. Vital Health Stat 2(205). 2024. DOI: https://dx.doi.org/10.15620/cdc:134958.

For sale by the U.S. Government Publishing Office
Superintendent of Documents
Mail Stop: SSOP
Washington, DC 20401–0001
Printed on acid-free paper.

NATIONAL CENTER FOR HEALTH STATISTICS

Vital and Health Statistics

Series 2, Number 205 January 2024

Validation of the Enhanced Opioid Identification and Co-occurring Disorders Algorithms

Data Evaluation and Methods Research

U.S. DEPARTMENT OF HEALTH AND HUMAN SERVICES
Centers for Disease Control and Prevention
National Center for Health Statistics

Hyattsville, Maryland
January 2024

Contents

Detailed Tables

Appendix

Validation of the Enhanced Opioid Identification and Co-occurring Disorders Algorithms

by Amy M. Brown, M.P.H., Donielle G. White, M.P.H., Nikki B. Adams, Ph.D., Rihem Badwe, PharmD, Salah Shaikh, M.P.H., and Lello Guluma, M.P.H.

Abstract

Objectives

This report documents the results of a validation study conducted to assess the reliability of two algorithms applied to the 2016 National Hospital Care Survey. One algorithm identifies opioid-involved and opioid overdose hospital encounters, and the other identifies encounters with patients that have substance use disorders and selected mental health issues. These algorithms use both medical codes and natural language processing to identify encounters.

Methods

To validate the algorithms, medical record abstraction was performed on a stratified sample of 900 hospital encounters from the 2016 National Hospital Care Survey. The abstractors recorded their determinations of opioid involvement, opioid overdose, substance use disorder, and mental health issues on a standard form. Abstractors' determinations were compared with algorithm output to assess the overall performance using *F*-score and Matthews correlation coefficient. The latter provided a secondary measure of performance. The 2016 National Hospital Care Survey data are unweighted and not nationally representative.

Results

Overall algorithm performance varied by topic and by metric. The opioid-involvement algorithm achieved the highest performance, performing well with an *F*-score of 0.95, followed by the substance use disorder algorithm (*F*-score of 0.79), the mental health issues algorithm (*F*-score of 0.68), and the opioid overdose algorithm (*F*-score of 0.48). Assessment by Matthews correlation coefficient indicated an overall poorer level of performance, ranging from a high of 0.57 for the mental health issues algorithm to a low of 0.33 for the opioid-involvement algorithm. The causes of false positives and false negatives likewise varied, including both overly broad code and keyword inclusions as well as incompleteness of data submitted to the National Hospital Care Survey.

Conclusion

The validation study illustrates which aspects of the developed algorithms performed well and which aspects should be altered or discarded in future iterations. It further emphasizes the importance of data completeness, therefore laying the groundwork for improvements to future survey analyses.

Keywords: mental health issues • substance use disorders • natural language processing • National Hospital Care Survey

Introduction

The National Hospital Care Survey (NHCS) is designed to provide accurate and reliable statistics on patient care in hospital-based settings to describe national patterns of healthcare delivery and use in the United States. However, while intended to make national estimates, the 2016 NHCS does not provide nationally representative data due to a low overall response rate of 27% for that survey year. Participating hospitals could submit two main sources of data, Uniform Bill (UB)-04 administrative claims or electronic health records (EHRs), which include unstructured clinical notes.

During fiscal years 2018 and 2019, the National Center for Health Statistics (NCHS) received funding from the U.S. Department of Health and Human Services, Office of the Secretary, Patient-Centered Outcomes Research Trust Fund to develop two algorithms that use all available structured and unstructured data elements accessible in NHCS data. The Enhanced Opioid Identification Algorithm

was designed to identify hospital encounters in NHCS that involve past or present use of opioids in any form (for example, as directed, misused, or taken accidentally), also referred to as opioid-involved encounters. The Co-occurring Disorders Algorithm was designed to identify lifetime diagnoses of both a substance use disorder (SUD) and a selected mental health issue (MHI), diagnosed in the past or during the present opioid-involved encounter. Both algorithms incorporate the use of natural language processing (NLP) techniques to analyze submitted clinical notes to identify cases not identified by medical code-only algorithms (1). Research on the process of identifying patients with diseases or conditions of interest has found that searches relying exclusively on standard medical codes, such as those used to identify diagnoses, procedures, and medications, may miss some true cases. This may be due to differences in coding practices across hospitals, as well as hospitals' selection of codes to maximize reimbursement when included on claims (2). Searches of both medical codes and clinical notes have been shown to improve algorithm performance (3–5).

NCHS has previously published two reports detailing the methodology used to create both algorithms. One-fifth of all identified opioid-involved encounters and 2.9% of identified opioid overdose encounters were exclusively flagged by the NLP component of the Enhanced Opioid Identification Algorithm (6). Similarly, the NLP component of the Co-occurring Disorders Algorithm identified 10% of encounters with co-occurring disorders that were not flagged by the code component (7).

The purpose of the current study is to validate the accuracy of both algorithms in distinguishing between true and false cases based on established case definitions and associated criteria. The performance of each algorithm was measured against the gold standard of medical record abstraction. This report shows overall performance metrics of these algorithms, as well as metrics by type of data source (administrative claims or EHR data) and algorithm component, as well as potential areas of improvement. Study limitations and future algorithm applications are also discussed.

Methodology

Study Sample

Encounters with opioid involvement were defined as those having evidence of any form of past or present use of opioids (including opium, heroin, methadone, and other opiates and related narcotics). Both licit and illicit forms of use were included. Encounters with opioid overdose were a subset of opioid-involved encounters with specific evidence of acute opioid toxicity or poisoning.

Encounters with SUD were defined as having evidence of a past or present SUD diagnosis (alcohol, opioid, cannabis, sedative, cocaine, other stimulants, hallucinogen, inhalant, tobacco, or other psychoactive substance-related disorders). Encounters with MHIs had evidence of past or present MHI diagnosis (anxiety, trauma, obsessive compulsive disorder, depression, or self-harm thoughts or behaviors). Each concept of the Co-occurring Disorders Algorithm, SUD and MHI, was independently developed and, therefore, examined separately. Flagged cases were identified by the medical code, NLP, or both components of the two algorithms. Cases with evidence of either SUD or MHI were then identified and counted.

A total of 158 noninstitutional, nonfederal hospitals with six or more staffed beds participated in the 2016 NHCS and submitted data on 9,624,026 emergency department and hospitalization encounters that occurred in the 2016 calendar year. The data are unweighted and are not nationally representative. Among emergency department visits, 805,456 encounters were identified by the algorithm as opioid involved and 74,472 encounters were identified as having co-occurring disorders (both an SUD and an MHI). Among inpatient hospitalizations, 565,371 opioid-involved encounters and 85,019 encounters with evidence of co-occurring disorders were observed.

More detailed information about the methodology for the code and NLP components of each algorithm is published elsewhere (6,7). Medical codes and search terms used in the Enhanced Opioid Identification Algorithm are available from: https://www.cdc.gov/nchs/data/nhcs/Task-3-Doc-508.pdf. Medical codes and search terms used in the Co-occurring Disorders Algorithm are available from: https://www.cdc.gov/rdc/data/b1/FY19-RDC-2021-Oct-508.pdf.

Fifty-three hospitals currently participating in NHCS were eligible for the validation study during the recruitment period from October 2020 to January 2021, representing diversity in several characteristics, including location, bed size, and EHR vendor. Nine hospitals agreed to provide remote access to medical records to allow clinicians to abstract data from a sample of hospital encounters. A stratified sampling design was used to select encounters across nine strata with and without evidence of the encounter types as identified by the code, NLP, or both components of the algorithms (Table 1). Eight of the nine strata indicated use of an opioid, resulting in an imbalanced data set. Matthews correlation coefficient (MCC), which is well suited for imbalanced data, was one of two measures used to assess overall algorithm performance. Performance measurement is discussed in greater detail in the Methodology section.

From each hospital, 150 encounters were randomly sampled across the 9 strata, creating a total sample size of 1,350 encounters. A subset of 20 encounters was reserved for quality control purposes and excluded from analysis. The remaining sample of 1,330 encounters was used to abstract up to 100 encounters from each hospital. An oversample was included to provide replacements for encounter records that could not be located or were

ineligible for abstraction due to technical issues. Between February 2021 and June 2021, 100 encounters were abstracted from 9 hospitals to create the final validation study sample of 900 encounters.

Table 2 shows characteristics of sampled encounters included in the validation study. Most encounters were with female patients (54.1%), and more than one-half were with those ages 30–64 years (57.3%). Most encounters occurred in the emergency department (77.2%) and in hospitals located in the Midwest census region (44.4%). No encounters from hospitals located in the West census region were included because no eligible hospitals from that region agreed to participate. A total of 55.6% of encounters were from hospitals that submitted administrative claims data to the 2016 NHCS and 44.4% of encounters were from hospitals that submitted EHR data.

Medical Record Abstraction

Medical record abstraction data were used as the gold standard against which algorithm results were compared. A structured medical record abstraction form was developed (Appendix), which was converted into a web-based tool to facilitate secure data entry and submission to a data repository for processing. Three experienced medical record abstractors with clinical backgrounds received training on study case definitions, a detailed abstraction guide, and the abstraction tool. This process also included an opportunity to practice using synthetic data patient charts with and without evidence of concepts of interest and compare the charts against a verified answer key. Abstractors received additional training on any observed discrepancies.

Following training, abstractors received credentials to remotely access EHR systems at assigned hospitals and then used prepopulated information within the abstraction tool to locate each sampled encounter. Prepopulated information included the patient's medical record number, setting (emergency department or inpatient), encounter dates, and patient information (date of birth, name, sex, and address). If the correct encounter could not be located within the EHR or available encounter records were not usable (illegible, missing key information), the abstractor could note this in the abstraction tool and then select a replacement encounter to abstract.

For each of the two primary abstractors, 10% of the encounters from their first assigned hospital were re-abstracted by a supervisory abstractor. Areas of disagreement were communicated back to primary abstractors for reconciliation and, if necessary, corrections were made. This process helped ensure greater adherence to the annotation criteria and allowed the primary abstractors to come to greater agreement before continuing independent annotation.

Algorithm Performance Standards

All abstracted data were combined into a SAS data set and reviewed by the study clinician to assign a final classification (that is, true case or not a true case) for each concept of interest, based on established case definitions and the abstraction guide. Algorithm performance was evaluated using sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), *F*-scores, and MCC to examine overall performance, performance by data source, and performance by algorithm component. Algorithm results were assessed against the abstraction results, which served as the gold standard or truth. All calculations were based on two-by-two contingency tables, where:

- Encounters flagged by the algorithm and identified by abstraction are true positives (TP);
- Encounters flagged by the algorithm but not identified by abstraction are false positives (FP);
- Encounters not flagged by the algorithm but identified by abstraction are false negatives (FN); and
- Encounters not flagged by the algorithm and not identified by abstraction are true negatives (TN).

Sensitivity was calculated as:

$$\text{Sensitivity} = \frac{true\ positives}{total\ true\ positives\ and\ false\ negatives}$$

When sensitivity is high, it means the algorithm flagged a high percentage of cases that were also classified as positive by medical record abstraction (meaning the case was identified as being an opioid-involved, SUD, or MHI encounter). When sensitivity is low, it means the algorithm missed many cases that were classified as positive by record abstraction.

Specificity was calculated as:

$$Specificity = \frac{true\ negatives}{total\ false\ positives\ and\ true\ negatives}$$

When specificity is high, it means that the algorithm flagged as negative a high percentage of cases that were classified as negative by medical record abstraction (meaning the case was not identified as being an opioid-involved, SUD, or MHI encounter). When specificity is low, it means the algorithm flagged as positive many cases classified as negative by abstraction. In contrast to sensitivity, which measures how well an algorithm finds positive cases, specificity measures how well an algorithm finds negative cases.

PPV was calculated as:

$$PPV = \frac{true\ positives}{total\ true\ positives\ and\ false\ positives}$$

When PPV is high, it means that when the algorithm flagged a case as positive, it was usually correct. When PPV is low, it means that many cases flagged as positive by the algorithm were not identified as an encounter by medical record abstraction.

NPV was calculated as:

$$NPV = \frac{true\ negatives}{total\ false\ negatives\ and\ true\ negatives}$$

In contrast to PPV, which measures the algorithm's accuracy in flagging positive cases, NPV measures the accuracy of the algorithm in flagging negative cases. When NPV is high, it means that when the algorithm flagged a case as negative, it was usually correct. When NPV is low, it means that the algorithm was more likely to miss cases identified by abstraction.

The *F*-score (also known as *F*1 score) was calculated as:

$$F\text{-score} = \frac{true\ positives}{true\ positives + \frac{1}{2}(false\ positives + false\ negatives)}$$

The *F*-score is the harmonic mean of PPV and sensitivity, with values ranging from 0 to 1, and is a common metric for assessing overall classification performance (8).

MCC was calculated as:

$$MCC = \frac{TP \bullet TN - FP \bullet FN}{\sqrt{(TP + FP) \bullet (TP + FN) \bullet (TN + FP) \bullet (TN + FN)}}$$

MCC (also known as Pearson's Phi coefficient) provides a measure balanced over true and false negatives and positives and can be used even when sample sizes in data classes are unevenly distributed (9).

F-scores were used as the primary measure to assess overall algorithm performance for each concept of interest, in part due to their widespread use across similar types of opioid classification studies (2,4,5,9). Additionally, *F*-scores provide an effective means of examining how well each algorithm identifies true cases, which was a high priority for the study. Performance standards were established based on a review of *F*-scores considered indicative of high performance in previous algorithm validation studies and expectations for how readily identifiable concepts of interest would be in the data set. *F*-scores that were greater than or equal to 0.80 were considered acceptable performance, and *F*-scores that were greater than or equal to 0.85 were considered excellent performance for opioid involvement, opioid overdose, SUD, and MHI. Due to the imbalance observed across most strata and concerns that *F*-scores may produce unreliable results with imbalanced data, MCC was selected as a secondary measure of overall performance (8–10). MCC is often preferred for imbalanced data because it uses all four quantities of the two-by-two contingency table (TP, TN, FP, and FN) (8,10). Note the lack of consensus on specific MCC thresholds used to evaluate performance (11). For this reason, no specific MCC performance thresholds were established.

Additional Analyses

Additional analyses were conducted for concepts of interest that did not meet excellent performance thresholds for identifying factors that may have impacted performance. The percent distribution of EHR sections where abstractors reported finding true positive and false negative cases is shown for each concept. Also, specific codes and keywords suspected to have contributed to poorer performance were further examined.

Results

Overall Performance

Table 3 shows the outcomes determined by the abstractors during the validation study for each concept of interest for the encounters identified by the Enhanced Opioid Identification Algorithm and Co-occurring Disorders Algorithm. From the 900 sampled encounters, 865 were identified as opioid involved by the algorithm and 802 were confirmed to be opioid involved by the abstractors. The abstractors also identified 15 opioid-involved encounters in the sample that were not found by the algorithm. Of the 188 opioid overdose encounters identified by the abstractors, 80 were also identified as opioid overdose encounters by the algorithm. The algorithm identified 63 encounters as opioid overdose that were not defined as overdose by the abstractors, and the abstractors identified 108 encounters as opioid overdose that were not identified by the algorithm.

Of the 525 SUD encounters identified by abstractors, 411 were also identified by the algorithm. The abstractors also identified 114 encounters as having SUD that were not found by the algorithm. Of the 243 MHI encounters identified by the algorithm, only 20 were confirmed to be missing an MHI by the abstractors. However, the abstractors identified 186 additional MHI encounters not identified by the algorithm.

Tables 4–6 show performance metrics for the algorithms across each concept of interest. *F*-score values that met an acceptable threshold of 0.80 are marked with "‡" and values that met the excellent threshold of ≥ 0.85 are marked with "†." Overall algorithm performance based on *F*-score for opioid involvement was excellent (0.95) (Table 4). MCC, however, was the lowest for this concept at 0.33, driven largely by low sensitivity (24.1%) and NPV (57.1%). None of the *F*-scores for opioid overdose (0.48), SUD (0.79), or MHI (0.68) reached an acceptable

level. The *F*-score for the SUD algorithm was very close to acceptable and its MCC was the second highest (0.51).

Low sensitivity (42.6%) and PPV (55.9%) for opioid overdose indicate that the algorithm misses over one-half of the opioid overdose encounters identified by abstraction. Findings showed that just over one-half of the opioid overdose encounters flagged by the algorithm were also identified by abstraction. These findings also resulted in the opioid-involvement algorithm having the second lowest MCC (0.33). For MHI, although PPV was high at 91.8% and MCC was the highest across all concepts of interest (0.57), the low sensitivity of 54.5% indicates that many MHI encounters identified by abstraction were missed by the algorithm.

Table 5 shows algorithm performance by data source. The opioid-involved algorithm performed well according to *F*-score across both data sources, achieving an excellent level *F*-score for both claims (0.98) and EHRs (0.92). However, MCC was lower for EHR data (0.24) compared with claims data (0.56) due to low specificity (11.1%). Opioid overdose did not meet minimum performance *F*-score standards for either source, with *F*-scores of 0.50 for claims and 0.46 for EHR. MCC performance was low both for claims (0.39) and EHRs (0.37). For SUD, the algorithm achieved the acceptable *F*-score level for claims (0.80), but just slightly below acceptable for EHRs (0.79). SUD performance on MCC was higher for claims data (0.61) than for EHRs (0.46). MHI did not meet acceptable *F*-score performance standards for either claims (0.72) or EHRs (0.62). MHI performance on MCC was also higher for claims data (0.60) compared with EHRs (0.51).

Table 6 shows the performance metrics for the medical code and NLP components of the algorithm. Opioid-involvement *F*-scores were acceptable for the code component (0.82) and excellent for the NLP component (0.88). However, opioid-involvement MCC scores were lower (0.10 for the code component and 0.33 for the NLP component), primarily based on a lower specificity of 15.0%. The opioid overdose, SUD, and MHI algorithms all failed to meet the minimum *F*-score performance thresholds and had comparatively lower MCC scores.

Findings From Additional Analyses

Additional analyses were performed for opioid overdose, SUD, and MHI because these concepts did not meet the established *F*-score target for excellent performance.

EHR Section

Table 7 shows EHR sections where abstractors found evidence for each concept of interest, including diagnosis codes and written indications, across all true positive cases. For opioid overdose, frequently reported sections included Diagnoses (80.0%), History of Present Illness (78.8%), and Assessment and Plan (46.3%). Abstractors also frequently found evidence of SUD true positives in the Diagnoses (77.9%), Social History (75.7%), and History of Present Illness (40.6%) sections. Finally, for MHI, common sections included Diagnoses (83.9%), Past Medical History (71.3%), and History of Present Illness (36.3%).

Table 8 summarizes EHR locations where abstractors were able to find evidence for each concept of interest across all false negative cases, which represented confirmed positive cases that were missed by the algorithms. Commonly reported EHR locations for opioid overdose false negatives were Diagnoses (87.0%), Assessment and Plan (36.1%), and History of Present Illness (34.3%). For SUD, they were Diagnoses (63.2%), Nurses Notes (36.0%), and Social History (30.7%). And for MHI, common sections included Diagnoses (73.7%), Past Medical History (61.8%), and History of Present Illness (19.4%).

Limitations

The data submitted for the 2016 NHCS have several previously reported limitations that may have impacted both the code and NLP components of the algorithms (6,7). The quality and completeness of clinical medical codes and the use of nonstandard coding systems may have hindered the performance of the algorithm's code component. The completeness and formatting of submitted clinical notes varied widely across hospitals. Although attempts were made to recruit nine hospitals that submitted EHR data to maximize data available to assess the NLP component, the COVID-19 pandemic hindered recruitment efforts, and only four hospitals that submitted EHR data to the 2016 NHCS could be secured; the remaining five hospitals were those that submitted administrative claims data. Additionally, less than one-half of all EHR encounters had notes available for analysis. As a result, the NLP component could only be applied to 344 (38.2%) of the 900 sampled encounters.

Accessibility to EHR data for abstraction varied among sampled hospitals. COVID-19 visitor restrictions prevented medical record abstraction from being conducted onsite as originally planned. The remote EHR interface was not uniform across participating hospitals due to different remote features offered by each EHR vendor. Sometimes, sections of the EHR were not accessible, making it difficult to distinguish the timing of diagnoses and medications. Two hospitals did not provide direct access to their EHR system but instead provided access to a limited data set containing records for the requested sampled patient encounters. Moreover, this data set included scanned versions of paper-based records rather than fully digitized and searchable records. Each record could be hundreds of pages long, and some handwritten notes were illegible and lacked full documentation for all diagnoses.

Finally, sample selection for the study primarily included encounters with evidence of opioid involvement or opioid overdose as identified by the algorithms, with a relatively small number of selected encounters with no such evidence,

resulting in an imbalanced data set. *F*-score and MCC distributions can both be skewed by imbalanced data, although MCC tends to be skewed to a lesser extent (11).

The sample selection strategy was intended to prioritize an examination of each algorithm's ability to identify true positive cases among the flagged encounters. Less importance was placed on assessing the ability of the algorithms to distinguish false negative cases, as many false negative cases were presumed to stem from a lack of data, either collected by the 2016 NHCS (described in more detail in the Discussion section) or inaccessible to abstractors for the study, rather than a flaw in the algorithm itself. In keeping with this focus, *F*-score was used as the primary measure of algorithm performance, which emphasizes positive cases and is heavily influenced by PPV (8). MCC, which weights positive and negative cases proportionally with respect to their prevalence in the data set, was used as a secondary measure. Although *F*-score is also influenced by prevalence, it does not attempt to weight according to prevalence like MCC.

Discussion

Opioid involvement was the only concept of interest to achieve an excellent level of overall performance based on *F*-score (0.95). The next best performance was SUD, which was just under the acceptable level at 0.79, followed by MHI at 0.68, and opioid overdose at 0.48. Performance on MCC was comparatively lower than *F*-score for each algorithm, ranging from 0.33 for opioid involvement to 0.57 for MHI, suggesting that *F*-scores may have been inflated by the impact of the data imbalance. These results also underscore the importance of collecting complete EHR data during the NHCS data collection. The occurrence of false positives from the algorithms may be due to either the algorithms finding codes and search terms in the NHCS data that were not found by abstractors in the final medical record, or a later determination by abstractors that flagged cases did not meet the case definitions in the absence of additional supporting evidence. False negatives, on the other hand, may have been due to a failure to include additional relevant codes and keywords in the algorithms' searches.

The remaining study analyses revealed specific areas of the opioid overdose, SUD, and MHI algorithms that could be adjusted to improve performance.

Opioid Overdose

Based on previous analyses conducted during algorithm development (6), opioid overdose was expected to be more challenging to identify compared with other concepts of interest. Inclusion and exclusion criteria to identify opioid overdose were selected to cast a wide net to capture all possible cases. However, the lower PPV, compared with the other outcomes, which is driven by false positives, indicates that a more restrictive search may have been warranted. The algorithm applied an exclusion of diagnosis codes and written indications for opioid overdose associated with dates that occurred before or after 2016. However, opioid overdoses without dates in the NHCS data set were included in the algorithm's search. The inclusion of dateless overdoses may have contributed to false positives that identified opioid overdoses that occurred outside of calendar year 2016, based on information found later in the full medical record but not in the NHCS data set. The majority (90.7%) of false positive overdose encounters flagged by the code component did not have a date available in NHCS-submitted data. In the claims data, some of these events may represent older opioid overdoses that were carried over from subsequent bills (1). And in the EHR data, sections such as the Problem List represent a running list of diagnoses assigned over time to the patient. It is critical to communicate to NHCS participating hospitals the importance of including complete date information in data extracted from EHR systems to ensure overdose events can be reliably attributed to the current encounter.

In addition to encounters with missing diagnoses dates, the medical codes used to search opioid overdoses may have been too broad. CDC's Drug Overdose Surveillance and Epidemiology (DOSE) system has a case definition for suspected opioid overdose based on diagnostic codes and key search terms. Only *International Classification of Diseases, 10th Revision, Clinical Modification* codes representing initial encounters for opioid poisoning are included (with a seventh character of A), while *International Classification of Diseases, 10th Revision, Clinical Modification* codes representing subsequent encounters (with a seventh character of D) or sequela (with a seventh character of S) are excluded because the latter do not represent new and acute overdose cases (12). The Enhanced Opioid Identification Algorithm included *International Classification of Diseases, 10th Revision, Clinical Modification* codes for all types of opioid poisoning encounters (initial, subsequent, and sequelae), including those that are excluded by the DOSE system. A future iteration of the algorithm that excludes subsequent and sequela encounters would help to narrowly target instances of acute opioid overdose.

In addition, DOSE searches are limited to emergency department discharge diagnoses and free text chief complaint notes (13). In our study, which includes both emergency department and inpatient data, the Diagnoses section was found to be the most common location for true positive and false negative cases, but Chief Complaint was infrequently identified by abstractors as the EHR location where they found evidence of an opioid overdose. Both the History of Present Illness and Assessment and Plan sections were more frequently cited locations. Results in Tables 7 and 8 could be used to inform decisions about which EHR locations to include or exclude in future algorithm searches for evidence of opioid overdose.

Note that the current version of the algorithm does not specifically find and exclude opioid overdoses related to in-hospital treatment that do not meet the intended case definition. This is of particular concern for inpatient hospitalizations involving surgery. Opioids are commonly administered to surgical patients for pain management and as part of the anesthesia process, and sometimes too large of a dose is administered. This could result in respiratory depression and other complications, followed by administration of naloxone to help reverse these effects (14). A simple exclusion of medical codes and written indications for opioid overdose near mentions of in-hospital naloxone administration within surgery-related medical notes may be sufficient to avoid flagging these cases. Alternatively, Green et al. has developed methods to identify inpatient opioid or oversedation events, which could be incorporated (15).

SUD

A review of false positive cases revealed that the algorithm flagged some encounters due to differential diagnoses of SUD, which represent *possible* conditions or diseases based on available information, before obtaining more confirmatory data to arrive at a final diagnosis. None of the existing SUD algorithm rule-outs are designed to detect and exclude differential diagnoses. An improvement to the algorithms should include the detection and exclusion of the qualifier differential near target diagnoses, as well as related phrases such as preliminary, presumptive, initial, tentative, and working.

Tobacco use disorder proved to be a particularly challenging SUD subcategory because it is often not documented in medical charts with explicit diagnostic codes or phrases, but rather usually includes only evidence of tobacco use behavior (for example, smoking, chewing, vaping) and qualifiers for frequency and duration. An earlier investigation of the NLP component for the SUD algorithm found a high false positive rate due to incorrectly flagged encounters for tobacco use disorder (7). In the current study, 61% of SUD false positive cases were flagged by the NLP component solely due to presence of the term "smoker" with no indication that the patient met requirements for tobacco use disorder as defined by the *Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition* or explicit diagnosis of nicotine dependence, which is used for coding purposes (16). The *Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition* definition involves a problematic pattern of tobacco use leading to clinically significant impairment or distress as manifested by having at least 2 out of a total of 11 criteria within a 12-month period (17). Although a more restrictive algorithm that excludes nonspecific references to the use of tobacco products would reduce false positives and, therefore, improve algorithm performance, it would also likely underestimate the occurrence of tobacco use disorder by missing many true cases that lack sufficient documentation for algorithm detection.

Future efforts could consider an alternative concept that is easier to measure, yet still clinically relevant for understanding co-occurring disorders among hospital patients who use opioids. Current smoking has been a frequently used measure in studies examining co-occurrence of smoking and opioid use (18). A meta-analysis of 10 observational studies found that current smokers had a pooled odds ratio of 2.51 for using opioids and an odds ratio of 8.23 for having opioid use disorder compared with nonsmokers (19). A broader concept for consideration would be current nicotine use, which would capture all forms of nicotine delivery. This is particularly important for emerging electronic cigarette (e-cigarette) products that can use nontobacco nicotine that is not made or derived from tobacco, such as synthetic nicotine (20). Most hospital EHRs include a Social History or equivalent section that documents nicotine use in structured or free-text fields. The History of Present Illness, Nurses Notes, and Past Medical History sections were also identified by abstractors as frequent EHR locations where this information was found.

MHI

A high number of false negatives (low sensitivity) was the primary driver of poor algorithm performance for MHI. While data from the Diagnoses section were commonly included in submitted NHCS data, this section did not include some diagnoses that were later accessible to the abstractors in the remote EHR interface. In addition, the other common EHR sections where abstractors reported finding false negative cases (that is, History of Present Illness, Past Medical History, Problem List, and Discharge Summary) were not consistently included in clinical notes submitted across participating hospitals and, therefore, would not have been available to be searched by the algorithm. These EHR sections will be specifically requested from participating NHCS hospitals, in addition to the most comprehensive list of all diagnoses associated with each encounter.

Two issues with the MHI NLP processor were also identified that resulted in classification errors, including: (1) improper sentence tokenization (that is, breaking chunks of text into sentences), which allowed sentence-level exclusions to be applied incorrectly, and (2) a regular expression that improperly excluded a set of capitalized keywords. One or both errors could have affected a single encounter, but, taken together, fixing these two issues would have correctly identified 37 MHI false negatives and improved sensitivity from 55.9% to 64.7% and the *F*-score from 0.71 to 0.78. Corrections for these two classification errors can be addressed in a future iteration of the algorithm.

Future Considerations

As a next step, the algorithms will be further refined to address areas of improvement identified in the validation study. In addition, participating hospitals are now required

to submit NHCS data according to standards documented in the "CDA R2 Implementation Guide: National Health Care Surveys (NHCS), R1 STU Release 3–US Realm, 2021," which identifies desired data elements and preferred formats to improve data completeness and standardization (21). EHR data quality should improve with use of these standards during data collection, which should ultimately improve performance of the NLP component of the algorithm. Additionally, with the increase in participating hospitals, NHCS will produce national estimates on hospital use and care. The refined algorithms can be applied to future years of NHCS data to generate national estimates of hospital encounters involving all forms of opioid use, opioid overdose, and co-occurring disorders for surveillance purposes.

References

1. Brown AM, DeFrances C, Crane E, Cai R, Naeger S. Identification of substance-involved emergency department visits using data from the National Hospital Care Survey. National Health Statistics Reports; no 114. Hyattsville, MD: National Center for Health Statistics. 2018.
2. Poulsen MN, Freda PJ, Troiani V, Davoudi A, Mowery DL. Classifying characteristics of opioid use disorder from hospital discharge summaries using natural language processing. Front Public Health 10:850619. 2022.
3. Wei W, Teixeira PL, Mo H, Cronin RM, Warner JL, Denny JC. Combining billing codes, clinical notes, and medications from electronic health records provides superior phenotyping performance. J Am Med Inform Assoc 23:e20–7. 2015.
4. Kashyap A, Callison-Burch C, Boland MR. A deep learning method to detect opioid prescription and opioid use disorder from electronic health records. Int J Med Inform 171:104979. 2022.
5. Blackley SV, MacPhaul E, Martin B, Song W, Suzuki J, Zhou L. Using natural language processing and machine learning to identify hospitalized patients with opioid use disorder. AMIA Annu Symp Proc 2020: 233–42. 2021.
6. White DG, Adams NB, Brown AM, O'Jiaku-Okorie A, Badwe R, Shaikh S, Adegboye A. Enhancing identification of opioid-involved health outcomes using National Hospital Care Survey data. National Center for Health Statistics. Vital Health Stat 2(188). 2021.
7. Brown AM, White DG, Adams NB, O'Jiaku-Okorie A, Badwe R, Shaikh S, Adegboye A. Identifying co-occurring mental health and substance abuse disorders among patients with an opioid-involved health encounter using National Hospital Care Survey data. National Center for Health Statistics. Vital Health Stat 2(193). 2022.
8. Chicco D, Jurman G. The advantages of the Matthews correlation coefficient (MCC) over F1 score and accuracy in binary classification evaluation. BMC Genomics 21(1):6. 2020.
9. Boughorbel S, Jarray F, El-Anbari M. Optimal classifier for imbalanced data using Matthews Correlation Coefficient metric. PLoS One 12(6):e0177678. 2017.
10. Zhu Q. On the performance of Matthews correlation coefficient (MCC) for imbalanced data set. Pattern Recognit Lett 136:71–80. 2020.
11. Green CA, Perrin NA, Hazlehurst B, Janoff SL, DeVeaugh-Geiss A, Carrell DS, et al. Identifying and classifying opioid-related overdoses: A validation study. Pharmacoepidemiol Drug Saf 28(8):1127–37. 2019.
12. Vivolo-Kantor AM, Pasalic E, Liu S, Martinez PD, Gladden RM. Defining indicators for drug overdose emergency department visits and hospitalisations in ICD–10–CM coded discharge data. Inj Prev 27(S1):i56–61. 2021.
13. Vivolo-Kantor AM, Smith IV H, Scholl L. Differences and similarities between emergency department syndromic surveillance and hospital discharge data for nonfatal drug overdose. Ann Epidemiol 62:43–50. 2021.
14. Brant JM, Stringer L, Jurkovich LR, Coombs NC, Mullette EJ, Buffington C, et al. Predictors of oversedation in hospitalized patients. Am J Health Syst Pharm 75(18):1378–85. 2018.
15. Green CA, Hazlehurst B, Brandes J, Sapp DS, Janoff SL, Coplan PM, DeVeaugh-Geiss A. Development of an algorithm to identify inpatient opioid-related overdoses and oversedation using electronic data. Pharmacoepidemiol Drug Saf 28(8):1138–42. 2019.
16. American Psychiatric Association. 2017 DSM-5 diagnoses and new ICD–10–CM codes. 2022. Available from: https://psychiatry.org/psychiatrists/practice/dsm/updates-to-dsm/coding-updates/2017-coding-updates.
17. American Psychiatric Association. Substance-related and addictive disorders. In: Diagnostic and statistical manual of mental disorders. 5th ed. Washington, D.C.: American Psychiatric Publishing. 2013.
18. Morris CD, Garver-Apgar CE. Nicotine and opioids: A call for co-treatment as the standard of care. J Behav Health Serv Res 47(4):601–13. 2020.
19. Rajabi A, Dehghani M, Shojaei A, Farjam M, Motevalian SA. Association between tobacco smoking and opioid use: A meta-analysis. Addict Behav 92:225–35. 2019.
20. U.S. Food and Drug Administration. Requirement for products made with non-tobacco nicotine take effect April 14, 2022. Available from: https://www.fda.gov/

tobacco-products/ctp-newsroom/requirements-products-made-non-tobacco-nicotine-take-effect-april-14.

21. HL7 International. HL7 CDA R2 implementation guide: National Health Care Surveys (NHCS), R1 STU release 3.1 – US realm. 2021. Available from: https://www.hl7.org/implement/standards/product_brief.cfm?product_id=385.

Detailed Tables

Table 1. Sampling strata used to identify encounters for medical record abstraction

Strata	Encounter type	Algorithm component
1.	Opioid-involved and MHI	NLP component only
2.	Opioid-involved and SUD	NLP component only
3.	Opioid-involved and no MHI or SUD	NLP component only
4.	Opioid-involved and MHI	Code component only
5.	Opioid-involved and SUD	Code component only
6.	Opioid-involved and no MHI or SUD	Code component only
7.	Opioid Overdose and MHI or SUD	Both components
8.	Opioid Overdose and no MHI or SUD	Both components
9.	Not opioid-involved and no opioid overdose	Both components

NOTES: MHI is mental health issue. SUD is substance use disorder. NLP is natural language processing.

SOURCE: National Center for Health Statistics, 2016 National Hospital Care Survey.

Table 2. Characteristics of sampled encounters in the validation study data set

Characteristic	Number	Percent
Patient sex		
Female	695	54.1
Male	205	45.9
Patient age		
0–17	53	5.9
18–29	154	17.1
30–49	300	33.3
50–64	216	24.0
65–84	158	17.6
85 and older	19	2.1
Hospital setting		
Emergency department	695	77.2
Inpatient department	205	22.8
Hospital region		
Northeast	200	22.2
Midwest	400	44.4
South	300	33.3
West	–	–
Data type submitted to the 2016 National Hospital Care Survey		
Claims	500	55.6
Electronic health record	400	44.4

– Quantity zero.

NOTES: All counts are from a total sample of 900 encounters. Percentages may not add to 100% due to rounding.

SOURCE: National Center for Health Statistics, 2016 National Hospital Care Survey.

Table 3. Agreement of counts among the Enhanced Opioid Identification Algorithm and medical record abstraction for each encounter type

Algorithm	Opioid involvement		Opioid overdose		Substance use disorder		Mental health issue	
	Abstractor positive	Abstractor negative	Abstractor positive	Abstractor negative	Abstractor positive	Abstractor negative	Abstractor positive	Abstractor negative
Algorithm positive	802	63	80	63	411	101	223	20
Algorithm negative	15	20	108	649	114	274	186	471

SOURCE: National Center for Health Statistics, 2016 National Hospital Care Survey.

Table 4. Overall algorithm performance metrics for each encounter type

Algorithm category	Sensitivity	Specificity	Positive predictive value	Negative predictive value	*F*-score	Matthews correlation coefficient
	Percent					
Opioid involvement	98.2	24.1	92.7	57.1	†0.95	0.33
Opioid overdose	42.6	91.2	55.9	85.7	0.48	0.38
Substance use disorder	78.3	73.1	80.3	70.6	0.79	0.51
Mental health issue	54.5	95.9	91.8	71.7	0.68	0.57

† Indicates concept of interest met an excellent level of performance.

SOURCE: National Center for Health Statistics, 2016 National Hospital Care Survey.

Table 5. Algorithm performance metrics for each encounter type, by data source

Algorithm category and performance metric	Administrative claims (n = 500)	Electronic health record (n = 400)
Opioid involvement		
Sensitivity percent	97.5	99.1
Specificity percent	65.0	11.1
PPV percent	98.5	85.6
NPV percent	52.0	70.0
F-score	†0.98	†0.92
MCC	0.56	0.24
Opioid overdose		
Sensitivity percent	39.4	51.0
Specificity percent	92.6	89.7
PPV percent	66.7	41.9
NPV percent	80.2	92.6
F-score	0.50	0.46
MCC	0.39	0.37
Substance use disorder		
Sensitivity percent	69.4	90.5
Specificity percent	92.9	51.4
PPV percent	93.8	69.7
NPV percent	66.2	81.4
F-score	‡0.80	0.79
MCC	0.61	0.46
Mental health issue		
Sensitivity percent	58.4	48.4
Specificity percent	96.8	95.0
PPV percent	94.8	86.5
NPV percent	69.9	73.6
F-score	0.72	0.62
MCC	0.60	0.51

† Indicates concept of interest met an excellent level of performance.
‡ Indicates concept of interest met an acceptable level of performance.

NOTES: PPV is positive predictive value. NPV is negative predictive value. MCC is Matthews correlation coefficient.

SOURCE: National Center for Health Statistics, 2016 National Hospital Care Survey.

Table 6. Algorithm performance metrics for each encounter type, by algorithm component

Algorithm category and performance metric	Code (n = 900)[1]	Natural language processing (n = 344)[2]
Opioid involvement		
Sensitivity percent	69.8	92.6
Specificity percent	85.5	15.0
PPV percent	97.9	83.8
NPV percent	22.3	30.0
F-score	†0.82	‡0.88
MCC	0.33	0.10
Opioid overdose		
Sensitivity percent	40.4	50.0
Specificity percent	94.0	92.0
PPV percent	63.9	39.0
NPV percent	85.7	94.7
F-score	0.50	0.44
MCC	0.41	0.38
Substance use disorder		
Sensitivity percent	63.4	97.2
Specificity percent	93.9	47.3
PPV percent	93.5	66.7
NPV percent	64.7	94.0
F-score	0.76	0.79
MCC	0.58	0.52
Mental health issue		
Sensitivity percent	46.7	50.0
Specificity percent	97.4	94.9
PPV percent	93.6	85.3
NPV percent	68.7	76.2
F-score	0.62	0.63
MCC	0.52	0.53

† Indicates concept of interest met an acceptable level of performance.
‡ Indicates concept of interest met an excellent level of performance.
[1]Includes all sampled encounters with at least one medical code record available in submitted survey data that could be searched by the code component (n = 900).
[2]Includes all sampled encounters with at least one clinical note record available in submitted survey data that could be searched by the NLP component (n = 344).

NOTES: PPV is positive predictive value. NPV is negative predictive value. MCC is Matthews correlation coefficient.

SOURCE: National Center for Health Statistics, 2016 National Hospital Care Survey.

Table 7. Percentage of true positive cases for each encounter type, by electronic health record section where evidence was found by abstractors

Electronic health record section	Opioid overdose (*n* = 80)	Substance use disorder (*n* = 411)	Mental health issue (*n* = 223)
Allergies	1.3	0.7	–
Assessment and plan	46.3	25.6	25.0
Chief complaint	13.8	4.9	6.3
Clinical summary	1.3	2.7	3.1
Consultation note	23.8	4.9	6.7
Diagnoses	80.0	77.9	83.9
Discharge summary	35.0	19.5	19.7
Emergency medical services report	5.0	0.7	1.4
Family history	–	–	–
History and physical	21.3	4.9	5.4
History of present illness	78.8	40.6	36.3
Impression	6.3	1.9	0.9
Lab or toxicology	7.5	8.3	–
Medication list	1.3	0.5	5.4
Nurses notes	31.3	12.9	10.8
Past medical history	16.3	32.1	71.3
Patient history report	–	4.1	1.8
Physical examination	1.3	0.5	0.9
Problem list	10.0	21.9	18.4
Progress note	28.8	13.9	15.7
Reason for visit	–	–	0.9
Review of systems	1.3	2.2	2.7
Services	–	–	–
Social history	16.3	75.7	0.9
Other	10.0	6.1	4.9

– Quantity zero.

NOTE: Electronic health record sections are not mutually exclusive.

SOURCE: National Center for Health Statistics, 2016 National Hospital Care Survey.

Table 8. Percentage of false negative cases for each encounter type, by electronic health record section where evidence was found by abstractors

Electronic health record section	Opioid overdose (*n* = 108)	Substance use disorder (*n* = 114)	Mental health issue (*n* = 186)
Allergies	7.4	–	–
Assessment and plan	36.1	12.3	10.2
Chief complaint	3.7	3.5	3.2
Clinical summary	0.9	0.9	1.6
Consultation note	22.2	11.4	9.7
Diagnoses	87.0	63.2	73.7
Discharge summary	21.3	10.5	12.4
Emergency medical services report	0.9	0.9	0.5
Family history	–	–	–
History and physical	13.9	13.2	8.1
History of present illness	34.3	19.3	19.4
Impression	0.9	2.6	1.1
Lab or toxicology	5.6	6.1	–
Medication list	9.3	1.8	2.7
Nurses notes	13.0	36.0	6.5
Past medical history	16.7	14.9	61.8
Patient history report	0.9	0.9	3.2
Physical examination	–	0.9	0.5
Problem list	18.5	15.8	17.7
Progress note	24.1	7.9	4.8
Reason for visit	–	–	0.5
Review of systems	–	1.8	2.2
Services	–	–	–
Social history	12.0	30.7	1.1
Other	5.6	2.6	6.5

– Quantity zero.

NOTE: Electronic health record sections are not mutually exclusive.

SOURCE: National Center for Health Statistics, 2016 National Hospital Care Survey.

Appendix. National Hospital Care Survey Abstraction Form

Validation of Enhanced Algorithms to Identify Opioid Use and Co-Occurring Disorders in National Hospital Care Survey (NHCS)

Abstraction Form

OMB No. 0920-0212; Expiration date 03/31/2022

Notice of Estimated Burden – CDC estimates the average public reporting burden for this collection of information as 30 minutes per response, including the time for reviewing instructions, searching existing data/information sources, gathering and maintaining the data/information needed, and completing and reviewing the collection of information. An agency may not conduct or sponsor, and a person is not required to respond to a collection of information unless it displays a currently valid OMB control number. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden to CDC/ATSDR Information Collection Review Office, 1600 Clifton Road NE, MS D-74, Atlanta, Georgia 30333; ATTN: PRA (0920-0212).

Assurance of Confidentiality – We take your privacy very seriously. All information that relates to or describes identifiable characteristics of individuals, a practice, or an establishment will be used only for statistical purposes. NCHS staff, contractors, and agents will not disclose or release responses in identifiable form without the consent of the individual or establishment in accordance with section 308(d) of the Public Health Service Act (42USC 242m) and the Confidential Information Protection and Statistical Efficiency Act (Title III of the Foundations for Evidence-Based Policymaking Act of 2018 (Pub. L. No. 115-435, 132 Stat. 5529)). In accordance with CIPSEA, every NCHS employee, contractor, and agent has taken an oath and is subject to a jail term of up to five years, a fine of up to $250,000, or both if he or she willfully discloses ANY identifiable information about you.

Use the below prepopulated information to locate the full medical record for the selected encounter in the hospital's EHR system. Verify that the correct medical record was selected before proceeding with abstraction.	
Hospital_ID	**XXXXXXXXXX**
Encounter_ID	**XXXXXXXXXX**
Medical Record Number (MRN)	**XXXXXXXXXXXXXXXXXXX**
Setting	☐ **Emergency Department (ED)** ☐ **Inpatient (IP)**
Encounter Start Date	**DD MON YYYY**
Encounter End Date	**DD MON YYYY**
Patient Date of Birth	**DD MON YYYY**
Patient Name	**LAST, FIRST MI**
Patient Sex	**XXXXXXXXXXXX**
Patient Address	**XXXXXXXXXXXX**

Answer all the following questions using only information found in the medical record for the above referenced encounter. Exclude encounters that occurred before or after the referenced encounter.

Question 1.	Response
Did the patient have at least one diagnosis related to past or present opioid use? (Select one)	☐ Yes ☐ No (Skip to Question 2)

Question 1a.	Response	
Which diagnosis related to past or present opioid use did the patient have? (Select all that apply) *NOTE: Includes a diagnosis code or a diagnostic phrase, such as a label or description for a diagnosis code.*	<u>Opioid related disorders</u> ☐ Opioid abuse ☐ Opioid dependence ☐ Opioid use <u>Poisoning by:</u> ☐ Opium ☐ Heroin ☐ Other opioids ☐ Methadone ☐ Other synthetic narcotics ☐ Unspecified narcotics ☐ Other narcotics <u>Adverse Effect of:</u> ☐ Opium ☐ Other opioids ☐ Methadone ☐ Other synthetic narcotics ☐ Unspecified narcotics ☐ Other narcotics	<u>Underdosing of:</u> ☐ Opium ☐ Other opioids ☐ Methadone ☐ Other synthetic narcotics ☐ Unspecified narcotics ☐ Other narcotics <u>Miscellaneous Opioid Use:</u> ☐ Long term current use of opiate analgesic ☐ Finding of opiate in blood ☐ Newborn affected by maternal use of opiates ☐ Neonatal withdrawal symptoms from maternal use of drugs of addiction ☐ Other (please specify) _____

Question 1b.	Response	
Where did you find evidence of a diagnosis related to past or present opioid use? (Select all that apply)	☐ Allergies ☐ Assessment & Plan ☐ Chief Complaint ☐ Diagnoses ☐ Discharge Summary ☐ EMS Report ☐ Family History ☐ History of Present Illness (HPI) ☐ Lab/Toxicology ☐ Medication List ☐ Nurses Notes	☐ Past Medical History ☐ Physical Examination ☐ Problem List ☐ Progress Note ☐ Reason for Visit ☐ Review of Systems ☐ Services ☐ Social History ☐ Other (please describe): _____

Question 2.	Response
Did the patient have at least one written indication of past or present opioid use stated by the patient or provider other than the diagnosis(es) indicated in question 1? (Select one)	☐ Yes ☐ No (Skip to Question 3)

Question 2a.	Response
Describe the written indication of past or present opioid use, copy verbatim from chart when possible. (Enter up to three) *NOTE: Excludes diagnosis(es) indicated in Question 1. Include information regarding the intent of the opioid use if documented in the record (e.g., unintentional/accidental, suicide attempt & intentional self-harm, assault).*	☐ Written indication 1 _____ ☐ Written indication 2 _____ ☐ Written indication 3 _____

Question 2b.	Response	
Where did you find evidence of the written indication of past or present opioid use? (Select all that apply)	☐ Allergies ☐ Assessment & Plan ☐ Chief Complaint ☐ Diagnoses ☐ Discharge Summary ☐ EMS Report ☐ Family History ☐ History of Present Illness (HPI) ☐ Lab/Toxicology ☐ Medication List ☐ Nurses Notes	☐ Past Medical History ☐ Physical Examination ☐ Problem List ☐ Progress Note ☐ Reason for Visit ☐ Review of Systems ☐ Services ☐ Social History ☐ Other (please describe): _____

Question 3.	Response
Was any drug testing performed during the encounter? (Select one)	☐ Yes ☐ No (Skip to Question 4)

Question 3a.	Response
Were any drug tests positive? (Select one)	☐ Yes ☐ No, negative for all tested substance (Skip to 3c) ☐ Don't know/No results provided (Skip to 4)

Question 3b.	Response	
Which substance(s) had positive test results? (Select all that apply)	☐ Amphetamines ☐ Barbiturates ☐ Benzodiazepines ☐ Buprenorphine/ Norbuprenorphine ☐ Cannabis/Marijuana (THC) ☐ Cocaine ☐ Codeine ☐ Ethanol/Alcohol ☐ Fentanyl/Fentanyl Analogs ☐ Heroin (6-AM & 6-MAM) ☐ Hydrocodone ☐ Hydromorphone ☐ Levorphanol	☐ Methadone ☐ Methamphetamine ☐ Mitragynine (Kratom) ☐ Morphine ☐ Naloxone ☐ Naltrexone ☐ Opiates ☐ Oxycodone ☐ Oxymorphone ☐ Phencyclidine (PCP) ☐ Tramadol ☐ Tricyclic antidepressants (TCA) ☐ Other (please describe) _____

Question 3c.	Response	
Where did you find evidence of drug testing? (Select all that apply)	☐ Allergies ☐ Assessment & Plan ☐ Chief Complaint ☐ Diagnoses ☐ Discharge Summary ☐ EMS Report ☐ Family History ☐ History of Present Illness (HPI) ☐ Lab/Toxicology ☐ Medication List ☐ Nurses Notes	☐ Past Medical History ☐ Physical Examination ☐ Problem List ☐ Progress Note ☐ Reason for Visit ☐ Review of Systems ☐ Services ☐ Social History ☐ Other (please describe): _____

Question 4.	Response
Was at least one prescription opioid administered and/or prescribed to the patient during the encounter or listed on Past or Current Medication Lists? (Select one)	☐ Yes ☐ No (Skip to Question 5)

Question 4a.	Response	
Which prescription opioid(s) was administered and/or prescribed to the patient? (Select all that apply)	☐ Buprenorphine ☐ Codeine ☐ Fentanyl ☐ Hydrocodone ☐ Hydromorphone ☐ Levorphanol ☐ Meperidine	☐ Methadone ☐ Morphine ☐ Oxycodone ☐ Oxymorphone ☐ Tramadol ☐ Other (please describe): _____

Question 4b.	Opioid	Response		
		Prior to Encounter	Given during Encounter	Prescribed upon Discharge
When was the prescription opioid(s) administered and/or prescribed to the patient? (Select all that apply) *NOTE: Opioids administered prior to encounter include those listed on Past and Current Medication Lists*	Buprenorphine		☐	☐
	Codeine	☐	☐	☐
	Fentanyl	☐	☐	☐
	Hydrocodone	☐	☐	☐
	Hydromorphone	☐	☐	☐
	Methadone	☐	☐	☐
	Morphine	☐	☐	☐
	Oxycodone	☐	☐	☐
	Oxymorphone	☐	☐	☐
	Tramadol	☐	☐	☐
	Other (please describe): _____	☐	☐	☐

Question 4c.	Response	
Where did you find evidence of opioid(s) administered and/or prescribed to the patient? (Select all that apply)	☐ Allergies ☐ Assessment & Plan ☐ Chief Complaint ☐ Diagnoses ☐ Discharge Summary ☐ EMS Report ☐ Family History ☐ History of Present Illness (HPI) ☐ Lab/Toxicology ☐ Medication List ☐ Nurses Notes	☐ Past Medical History ☐ Physical Examination ☐ Problem List ☐ Progress Note ☐ Reason for Visit ☐ Review of Systems ☐ Services ☐ Social History ☐ Other (please describe): _____

Question 5.	Response
Was naloxone (Narcan) administered to the patient either during the encounter or shortly before arrival? (Select one)	☐ Yes ☐ No (Skip to Question 6) ☐ Unknown (Skip to Question 6)

Question 5a.	Response
Who administered naloxone (Narcan)? (Select all that apply)	☐ EMS ☐ Firefighter ☐ Law enforcement ☐ Hospital provider ☐ Family/friend/bystander ☐ Other ☐ Unknown

Question 5b.	Response
How many doses of naloxone (Narcan) were administered? (Select one)	☐ Single ☐ Multiple ☐ Unknown

Question 5c.	Response
Did naloxone (Narcan) administration result in a positive response (e.g., increased respiration and/or increased alertness)? (Select one)	☐ Yes ☐ No ☐ Unknown

Question 5d.	Response	
Where did you find evidence of naloxone (Narcan) administration? (Select all that apply)	☐ Allergies ☐ Assessment & Plan ☐ Chief Complaint ☐ Diagnoses ☐ Discharge Summary ☐ EMS Report ☐ Family History ☐ History of Present Illness (HPI) ☐ Lab/Toxicology ☐ Medication List ☐ Nurses Notes	☐ Past Medical History ☐ Physical Examination ☐ Problem List ☐ Progress Note ☐ Reason for Visit ☐ Review of Systems ☐ Services ☐ Social History ☐ Other (please describe): _____

Question 6.	Response
Did the patient have at least one diagnosis related to a past or present substance use disorder? (Select one) *NOTE: Includes a diagnosis code or a diagnostic phrase, such as a label or description for a diagnosis code.*	☐ Yes ☐ No (Skip to Question 7)

Question 6a.	Response
Which diagnosis related to a past or present substance use disorder did the patient have? (Select all that apply) *NOTE: Includes a diagnosis code or a diagnostic phrase, such as a label or description for a diagnosis code.*	☐ Alcohol related disorders ☐ Opioid related disorders ☐ Cannabis related disorders ☐ Sedative, hypnotic or anxiolytic related disorders ☐ Cocaine related disorders ☐ Other stimulant related disorders ☐ Hallucinogen related disorders ☐ Nicotine dependence ☐ Inhalant related disorders ☐ Other psychoactive substance related disorders ☐ Other (please describe): _____

Question 6b.	Response	
Where did you find evidence of a diagnosis related to past or present substance use disorder? (Select all that apply)	☐ Allergies ☐ Assessment & Plan ☐ Chief Complaint ☐ Diagnoses ☐ Discharge Summary ☐ EMS Report ☐ Family History ☐ History of Present Illness (HPI) ☐ Lab/Toxicology ☐ Medication List ☐ Nurses Notes	☐ Past Medical History ☐ Physical Examination ☐ Problem List ☐ Progress Note ☐ Reason for Visit ☐ Review of Systems ☐ Services ☐ Social History ☐ Other (please describe): _____

Question 7.	Response
Was there at least one written indication of past or present substance use disorder stated by the patient or provider other than the diagnosis(es) indicated in question 6? (Select one)	☐ Yes ☐ No (Skip to Question 8)

Question 7a.	Response
Describe the written indication of a past or present substance use disorder, copy verbatim from chart when possible. (Enter up to three) *NOTE: Excludes diagnosis(es) indicated in Question 6.*	☐ Written indication 1 _____ ☐ Written indication 2 _____ ☐ Written indication 3 _____

Question 7b.	Response	
Where did you find evidence of a written indication of a past or present substance use disorder? (Select all that apply) *NOTE: Excludes diagnosis(es) indicated in Question 6.*	☐ Allergies ☐ Assessment & Plan ☐ Chief Complaint ☐ Diagnoses ☐ Discharge Summary ☐ EMS Report ☐ Family History ☐ History of Present Illness (HPI) ☐ Lab/Toxicology ☐ Medication List ☐ Nurses Notes	☐ Past Medical History ☐ Physical Examination ☐ Problem List ☐ Progress Note ☐ Reason for Visit ☐ Review of Systems ☐ Services ☐ Social History ☐ Other (please describe): _____

Question 8.	Response
Did the patient have at least one diagnosis related to a past or present anxiety disorder? (Select one) *NOTE: Includes a diagnosis code or a diagnostic phrase, such as a label or description for a diagnosis code.*	☐ Yes ☐ No (Skip to Question 9)

Question 8a.	Response
Which diagnosis related to a past or present anxiety disorder did the patient have? (Select all that apply) *NOTE: Includes a diagnosis code or a diagnostic phrase, such as a label or description for a diagnosis code.*	☐ Social phobias ☐ Panic disorder ☐ Generalized anxiety disorder ☐ Other anxiety disorders ☐ Obsessive-compulsive disorder ☐ Acute stress reaction ☐ Post-traumatic stress disorder (PTSD) ☐ Other (please describe): _____

Question 8b.	Response	
Where did you find evidence of a diagnosis related to a past or present anxiety disorder? (Select all that apply)	☐ Allergies ☐ Assessment & Plan ☐ Chief Complaint ☐ Diagnoses ☐ Discharge Summary ☐ EMS Report ☐ Family History ☐ History of Present Illness (HPI) ☐ Lab/Toxicology ☐ Medication List ☐ Nurses Notes	☐ Past Medical History ☐ Physical Examination ☐ Problem List ☐ Progress Note ☐ Reason for Visit ☐ Review of Systems ☐ Services ☐ Social History ☐ Other (please describe): _____

Question 9.	Response
Was there at least one written indication of past or present anxiety disorder stated by the patient or provider other than the diagnosis indicated in question 8? (Select one)	☐ Yes ☐ No (Skip to Question 10)

Question 9a.	Response
Describe the written indication of a past or present anxiety disorder, copy verbatim from chart when possible. (Enter up to three) ***NOTE: Excludes diagnosis(es) indicated in Question 8.***	☐ **Written indication 1 _____** ☐ **Written indication 2 _____** ☐ **Written indication 3 _____**

Question 9b.	Response	
Where did you find evidence of a written indication of a past or present anxiety disorder? (Select all that apply) ***NOTE: Excludes diagnosis(es) indicated in Question 8.***	☐ **Allergies** ☐ **Assessment & Plan** ☐ **Chief Complaint** ☐ **Diagnoses** ☐ **Discharge Summary** ☐ **EMS Report** ☐ **Family History** ☐ **History of Present Illness (HPI)** ☐ **Lab/Toxicology** ☐ **Medication List** ☐ **Nurses Notes**	☐ **Past Medical History** ☐ **Physical Examination** ☐ **Problem List** ☐ **Progress Note** ☐ **Reason for Visit** ☐ **Review of Systems** ☐ **Services** ☐ **Social History** ☐ **Other (please describe):** **_____**

Question 10.	Response
Was there at least one diagnosis related to a past or present depressive disorder? (Select one) ***NOTE: Includes a diagnosis code or a diagnostic phrase, such as a label or description for a diagnosis code.***	☐ **Yes** ☐ **No (Skip to Question 11)**

Question 10a.	Response
Which diagnosis related to a past or present depressive disorder did the patient have? (Select all that apply) ***NOTE: Includes a diagnosis code or a diagnostic phrase, such as a label or description for a diagnosis code.***	☐ **Major depressive disorder, single episode** ☐ **Major depressive disorder, recurrent** ☐ **Personal history of self-harm** ☐ **Suicidal ideations** ☐ **Suicide attempt** ☐ **Other (please describe):** **_____**

Question 10b.	Response	
Where did you find evidence of a diagnosis related to a past or present depressive disorder? (Select all that apply)	☐ Allergies ☐ Assessment & Plan ☐ Chief Complaint ☐ Diagnoses ☐ Discharge Summary ☐ EMS Report ☐ Family History ☐ History of Present Illness (HPI) ☐ Lab/Toxicology ☐ Medication List ☐ Nurses Notes	☐ Past Medical History ☐ Physical Examination ☐ Problem List ☐ Progress Note ☐ Reason for Visit ☐ Review of Systems ☐ Services ☐ Social History ☐ Other (please describe): _____

Question 11.	Response
Was there at least one written indication of past or present depressive disorder as stated by the patient or provider other than the diagnosis indicated in question 10? (Select one)	☐ Yes ☐ No (Skip to Question 12)

Question 11a.	Response
Describe the written indication of a past or present depressive disorder, copy verbatim from chart when possible. (Enter up to three) *NOTE: Excludes diagnosis(es) indicated in Question 10. For written indications of self-harm thoughts and behaviors, include whether they were related to a comorbidity of schizophrenia if documented in the record.*	☐ Written indication 1 _____ ☐ Written indication 2 _____ ☐ Written indication 3 _____

Question 11b.	Response	
Where did you find evidence of a written indication of a past or present depressive disorder? (Select all that apply) *NOTE: Excludes diagnosis(es) indicated in Question 10.*	☐ Allergies ☐ Assessment & Plan ☐ Chief Complaint ☐ Diagnoses ☐ Discharge Summary ☐ EMS Report ☐ Family History ☐ History of Present Illness (HPI) ☐ Lab/Toxicology ☐ Medication List ☐ Nurses Notes	☐ Past Medical History ☐ Physical Examination ☐ Problem List ☐ Progress Note ☐ Reason for Visit ☐ Review of Systems ☐ Services ☐ Social History ☐ Other (please describe): _____

Question 12.	Response
Was any treatment initiated for the patient's substance use disorder (SUD), anxiety disorder and/or depressive disorder during this encounter? (Select one)	☐ Yes ☐ No (Skip to Question 13) ☐ N/A, patient does not have a substance use disorder, anxiety disorder or depressive disorder (Skip to 13)

Question 12a.	Response	
What treatment was initiated during this encounter? (Select all that apply)	☐ Buprenorphine, Methadone or Naltrexone ☐ Admitted to a chemical dependency/detoxification unit at the hospital ☐ Psychotropic medication	☐ Admitted to a psychiatric inpatient unit at this hospital ☐ Brief intervention counseling ☐ Transferred/referred to another facility ☐ Other (please describe): _____

Question 12b.	Response	
Where did you find evidence of treatment initiated during this encounter? (Select all that apply)	☐ Allergies ☐ Assessment & Plan ☐ Chief Complaint ☐ Diagnoses ☐ Discharge Summary ☐ EMS Report ☐ Family History ☐ History of Present Illness (HPI) ☐ Lab/Toxicology ☐ Medication List ☐ Nurses Notes	☐ Past Medical History ☐ Physical Examination ☐ Problem List ☐ Progress Note ☐ Reason for Visit ☐ Review of Systems ☐ Services ☐ Social History ☐ Other (please describe): _____

Question 13.	Response
Abstractor Notes *Use this space to describe any issues with abstracting information for this encounter or any other pertinent information.*	

Vital and Health Statistics Series Descriptions

Active Series

Series 1. **Programs and Collection Procedures**
Reports describe the programs and data systems of the National Center for Health Statistics, and the data collection and survey methods used. Series 1 reports also include definitions, survey design, estimation, and other material necessary for understanding and analyzing the data.

Series 2. **Data Evaluation and Methods Research**
Reports present new statistical methodology including experimental tests of new survey methods, studies of vital and health statistics collection methods, new analytical techniques, objective evaluations of reliability of collected data, and contributions to statistical theory. Reports also include comparison of U.S. methodology with those of other countries.

Series 3. **Analytical and Epidemiological Studies**
Reports present data analyses, epidemiological studies, and descriptive statistics based on national surveys and data systems. As of 2015, Series 3 includes reports that would have previously been published in Series 5, 10–15, and 20–23.

Discontinued Series

Series 4. **Documents and Committee Reports**
Reports contain findings of major committees concerned with vital and health statistics and documents. The last Series 4 report was published in 2002; these are now included in Series 2 or another appropriate series.

Series 5. **International Vital and Health Statistics Reports**
Reports present analytical and descriptive comparisons of U.S. vital and health statistics with those of other countries. The last Series 5 report was published in 2003; these are now included in Series 3 or another appropriate series.

Series 6. **Cognition and Survey Measurement**
Reports use methods of cognitive science to design, evaluate, and test survey instruments. The last Series 6 report was published in 1999; these are now included in Series 2.

Series 10. **Data From the National Health Interview Survey**
Reports present statistics on illness; accidental injuries; disability; use of hospital, medical, dental, and other services; and other health-related topics. As of 2015, these are included in Series 3.

Series 11. **Data From the National Health Examination Survey, the National Health and Nutrition Examination Surveys, and the Hispanic Health and Nutrition Examination Survey**
Reports present 1) estimates of the medically defined prevalence of specific diseases in the United States and the distribution of the population with respect to physical, physiological, and psychological characteristics and 2) analysis of relationships among the various measurements. As of 2015, these are included in Series 3.

Series 12. **Data From the Institutionalized Population Surveys**
The last Series 12 report was published in 1974; these reports were included in Series 13, and as of 2015 are in Series 3.

Series 13. **Data From the National Health Care Survey**
Reports present statistics on health resources and use of health care resources based on data collected from health care providers and provider records. As of 2015, these reports are included in Series 3.

Series 14. **Data on Health Resources: Manpower and Facilities**
The last Series 14 report was published in 1989; these reports were included in Series 13, and are now included in Series 3.

Series 15. **Data From Special Surveys**
Reports contain statistics on health and health-related topics from surveys that are not a part of the continuing data systems of the National Center for Health Statistics. The last Series 15 report was published in 2002; these reports are now included in Series 3.

Series 16. **Compilations of Advance Data From Vital and Health Statistics**
The last Series 16 report was published in 1996. All reports are available online; compilations are no longer needed.

Series 20. **Data on Mortality**
Reports include analyses by cause of death and demographic variables, and geographic and trend analyses. The last Series 20 report was published in 2007; these reports are now included in Series 3.

Series 21. **Data on Natality, Marriage, and Divorce**
Reports include analyses by health and demographic variables, and geographic and trend analyses. The last Series 21 report was published in 2006; these reports are now included in Series 3.

Series 22. **Data From the National Mortality and Natality Surveys**
The last Series 22 report was published in 1973. Reports from sample surveys of vital records were included in Series 20 or 21, and are now included in Series 3.

Series 23. **Data From the National Survey of Family Growth**
Reports contain statistics on factors that affect birth rates, factors affecting the formation and dissolution of families, and behavior related to the risk of HIV and other sexually transmitted diseases. The last Series 23 report was published in 2011; these reports are now included in Series 3.

Series 24. **Compilations of Data on Natality, Mortality, Marriage, and Divorce**
The last Series 24 report was published in 1996. All reports are available online; compilations are no longer needed.

For answers to questions about this report or for a list of reports published in these series, contact:

Information Dissemination Staff
National Center for Health Statistics
Centers for Disease Control and Prevention
3311 Toledo Road, Room 4551, MS P08
Hyattsville, MD 20782

Tel: 1–800–CDC–INFO (1–800–232–4636)
TTY: 1–888–232–6348
Internet: https://www.cdc.gov/nchs
Online request form: https://www.cdc.gov/info
For e-mail updates on NCHS publication releases, subscribe online at: https://www.cdc.gov/nchs/email-updates.htm.

U.S. DEPARTMENT OF HEALTH & HUMAN SERVICES

Centers for Disease Control and Prevention
National Center for Health Statistics
3311 Toledo Road, Room 4551, MS P08
Hyattsville, MD 20782–2064

For more NCHS Series Reports, visit:
https://www.cdc.gov/nchs/products/series.htm

Series 2, No. 205
CS345710