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## Prescription Opioid Dependence in Western New York: Using Data Analytics to Find an Answer to the Opioid Epidemic

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### Abstract

Opioid dependence and overdose is on the rise. One indicator is the increasing trends of prescription buprenorphine use among patient on chronic pain medication. In addition to the New York State Department of Health's prescription drug monitoring programs and training programs for providers and first responders to detect and treat a narcotic overdose, further examination of the population may provide important information for multidisciplinary interventions to address this epidemic. This paper uses an observational database with a Natural Language Processing (NLP) based Not Only Structured Query Language architecture to examine Electronic Health Record (EHR) data at a regional level to study the trends of prescription opioid dependence. We aim to help prioritize interventions in vulnerable population subgroups. This study provides a report of the demographic patterns of opioid dependent patients in Western New York using High Throughput Phenotyping NLP of EHR data.

### Keywords

Substance-Related Disorders; Prescriptions; Natural Language Processing

### Introduction

Dependence and abuse of prescription opioid pain medication has substantially increased over the last decade. The rise in opioid dependence contributes to the rising prescription drug overdose deaths over the last decade. In 2014, approximately 1.3 million adults aged 26 or older had a pain medication use disorder in the past year. According to the 2014 National Survey on Drug Use and Health, published by the Substance Abuse and Mental Health

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Service Administration (SAMSA) about 0.6 percent of the population aged 26 or older were opioid dependent [1].

New York State has seen a steady rise in opioid related deaths from 1 per 100,000 people in 2010 to 4.2 per 100,000 people in 2013 [2]. This is considerably higher than many other states in the United States. The state health department is taking steps towards controlling this epidemic by training first responders, fire fighters and local health officials to recognize and treat opioid related overdoses. The non-medical use of prescription drugs has been on the rise among persons 12 years and older. This has led to the challenge of clinicians treating patients with chronic pain and the decision to treat the pain with opioid medications.

The New York State Department of Health (NYSDOH) implemented a prescription drug monitoring program, I-STOP, in August 2013. This gives the prescribing providers a secure access to the patients' registry of class II, III and IV controlled substance medication, which they are expected to consult before ordering any prescription pain medications. In 2016 NYSDOH implemented an amendment to the New York State Public Health Law §3331, that limits the prescription of controlled substances duration to seven days for the first prescription of narcotics for an acute pain condition [3].

There are many studies on the risk of opioid abuse and overdose among opioid dependent people [4, 5]. In March 2016, the Centers for Disease Control and Prevention (CDC) published chronic pain medications prescribing guidelines which presented an evidence based approach to patient assessment and prescription opioid monitoring tools [6].

On reviewing recent clinical evidence with an aim to propose adequate guidelines for prescription of pain medication the CDC concluded that there is insufficient evidence of effectiveness of long term opioid use for chronic pain [7]. In addition there is evidence of increased risk of overdose among patients using Methadone for long term opioid therapy or dependence [8]. Long term prescription opioid therapy for acute pain indications may result in higher incidence of opioid dependence [9, 10].

Knowledge about the epidemiology of local opioid dependent people may enable health care providers and population health workers to take proper actions. We used our web server based Natural Language processing (NLP) system to identify the cases of opioid dependence among our primary care clinic population in the Western New York (WNY) area.

The study of the distribution and determinants of opioid dependence among patients who are treated with chronic pain medications prescribed by their healthcare providers would aid in answering some key questions about potential abuse and overdose on opioids. The descriptive epidemiology of opioid dependence would help in identifying vulnerable age groups, gender, race, ethnicity, regional distribution and type of opioid pain medications, that more commonly result in dependence.

## Methods

### Technology

We implemented an Observational Medical Outcomes Partnership / Observational Health Data Sciences and Informatics (OMOP / OHDSI) database, to hold structured EHR data from local area primary care clinics managed by Allscripts company. We also created a high throughput phenotyping, NLP system, which can parse 7 million clinical notes in 1.5 hours. This runs as a web service and provides a modular component based NLP system. After the full semantic parse, we match the content against any number of ontologies. For each match, we tagged it as either a positive, negative, or uncertain assertion. We then performed automated compositional expressions. We stored the codes in a Berkeley database (BDB) NOSQL database, and the compositional expressions are stored in Neo4J (a graph database) and Graph DB (a triple store). This flexibility allows rapid retrieval of complex questions in real time.

In comparing the NOSQL database's retrieval times to SQL queries with either Oracle or SQL Server, we found the NOSQL database to improve performance between 100–1000 fold. Bio surveillance of influenza from clinical encounter notes using this NLP system has been shown to be superior to the conventional tools of surveillance, by Elkin et. al in *Ann. Int. Med.* 2012 [11]. Evidence of effective monitoring tools for post-operative complication in patients in the VA hospital systems with this method has also been published in *JAMA*, 2011 [12].

### Analysis

The retrospective analysis of EHR data from local clinic patients was performed using queries on the problem list, demographic data and medication list of all the patients in the data base. The OMOP/OHDSI data base was collected from Allscripts EHRs from 2010 to 2015. This common data model helps in the systematic analysis of disparate observational data bases of clinic records from the primary care and family medicine clinics in WNY region.

The database contained 212,343 patient records that were parsed and deidentified. Specific research IDs were assigned to each of the patient records and stored in a secure firewalled device for data analytics. The entire 212,343 records were queried for opioid dependence from the ICD9 and 10 diagnostic codes and SNOMED CT codes mapped to both the clinical notes and the problem list for each patient based on the mapped ICD and SNOMED CT codes. 1356 patients were identified as to having opioid dependence. Based on the age distribution (age range of 19 to 89 years) the population was divided into eight age groups (Table 1).

### High Throughput Phenotyping

The High-Throughput Phenotyping (HTP)-NLP subsystem is a software that produces, given biomedical text, semantic annotations of the text. The semantic annotations identify conceptual entities - their attributes, the relations they have with other entities and the events they participate in, as expressed in the input text. The conceptual entities, relations,

attributes, and events identified are specified by various knowledge representations as documented in Coding Sources. Examples of coding sources are medical terminologies [e.g., SNOMED CT, RxNorm, LOINC) and open biomedical ontologies foundry ontologies, e.g. Gene ontology, Functional Model of Anatomy]. The annotation results may be displayed or output in formats suitable for further processing. Entity identified is assigned a truth value from zero to one. Values from the text are assigned to entities from ontologies such as SNOMED CT. Where applicable data were combined into post-coordinated compositional expressions. These are fit into clinical models such as a) Course of Illness, b) Course of Treatment, and c) Course of Hospitalization. This method provides the most accurate NLP solution for health available based on published numbers. It is the only system that handles uncertainty and handles automated post-coordination which has been proven to be required for 41% of the problems with which clinicians commonly have to deal [13]. The system will be used to generate semantic triples for use in referent tracking and overlaying of clinical research models.

## Results

Of the 212,343 patients in the database, 1356 patients revealed opioid dependence on the problem list, ICD9–10 codes and prescription opioid pain medication with or without Buprenorphine or Suboxone in the medication list. The prevalence of opioid dependence in the clinic population was 0.64% (95% CI:0.61%-0.67%) over a five-year period.

The highest numbers of opioid dependence were seen in the 29 to 38 years' age group. That comprised 39.38% (95% CI: 36.78% to 41.98%) of the total opioid dependent population but accounted for only 2.03% of whole clinic population in this age group (95% CI:1.86% to 2.2%) (Table 1).

The subjects were then stratified by gender, race and ethnicity. There were 1005 patients with opioid dependence, among the Non-Hispanic population (total number 108,402).

Among the white Non-Hispanic population with opioid dependence, 41.33% (95% CI: 38.27% to 44.39%) were 29–38years old. The next common age group among the White Non-Hispanic opioid dependent subjects was 19 – 28 years, comprising of 22.48% (95% CI: 19.88% to 25.08%) of the total number of white Non-Hispanic or Latino opioid dependent population (Figure 1) (Table 2).

A total of 35/1356 patients with opioid dependence were from the Hispanic community. The rest of the 311 opioid dependent patients in the clinic did not have any race ethnicity records. The distribution of opioid dependence among the Hispanic population is shown in Figure 2.

We also queried the database to identify the names and quantity of opioid medication(s) used and the provider identification numbers associated with that prescriptions. The most commonly written prescription pain medication was of Hydrocodone Acetaminophen 7.5–500 mg tablets. The providers writing the most prescriptions could also be identified based on the provider identification numbers (Table 3). This information can be useful in following providers with a higher rate of prescription for opioid pain medications. The first three

numbers of the zip codes were obtained for these patients and one particular area was found to be more affected than others (Figure 3).

## Discussion

The trends of opioid dependence among the WNY clinic population in our study indicate that the prevalence is more in a certain section of the population. The predominance is among the Non-Hispanic, white population in the 19 to 38 years of age group. The prevalence in younger age implies that the complications related to opioid dependence would become a costly burden of disease for a longer duration of time. The prevalence of dependence in this clinic population will rise if this trend continues. Interventions at curbing prescription opioid dependence is necessary in this area.

The recent CDC [7] and SAMSHA [1] reports on drug overdose related deaths all indicate the urgent need to have a multidisciplinary approach for guidelines implementation, access to medication assisted treatment programs and naloxone training and distribution to first responders. In order to prevent overdose related deaths our HTP-NLP method of knowledge extraction from EHR is useful in cost effective and timely implementation of intervention.

There is a significant body of evidence indicating that short term acute pain medication prescriptions can lead to opioid dependence [9,10]. In addition, more people die of overdoses from prescription medication than from heroin, which is a rapidly growing problem [4, 6, 8].

Observational databases with codified data from the clinical notes using standardized ontologies such as SNOMED CT can be very useful for identifying problems of high socioeconomic impact, like prescription opioid addiction. NOSQL databases can make accessing large databases with billions of values practical for real time retrieval. We have knowledge from prior studies that robust ontology based SNOMED CT has good coverage of clinical thoughts and concepts in terms of surveillance [11, 12]. This study paves the way towards further development of real time bio surveillance with the tools of informatics.

There were a few limitations to this study. As it was a retrospective study on an existing database, the time to create an expert system and testing it out was not factored in. The dates and exact duration of the prescribed medications were not available. The indication for prescription and duration of symptoms were not clear. The question of potential illicit drug abuse or access and availability of methadone or buprenorphine for medication assisted treatment is not known. The potential confounders of alcoholism, smoking and or history of major depressive episodes were not taken into consideration. We assumed these are distributed uniformly over age groups, ethnicity, race and geographic distribution.

## Conclusions

This was a retrospective analysis of provider EHR data from local WNY area primary care clinics looking at the epidemiology of the opioid dependent population, the rate of opioid prescriptions that may be monitored through the EHRs and the geographic distribution of the population in question. This could provide insights into patient care patterns on a real

time basis. The distribution of the opioid dependent population identified in this study indicate a disparity by age, ethnicity and race. The geographical distribution of the dependent population shows a peak in a particular region. These informations could be used to allocate resources for special preventive programs in these areas.

The young age of many of the addicted patients gives rise to the question whether legitimate opioid prescriptions are leading these age groups towards addiction. This emphasises the need for routine screening for substance abuse in patients who are on opioid pain medications. The evidence of overdose and risk of abuse with other illicit agents in this population indicate the needs for realtime intervention among opioid dependent population. Future health informatics based research should be directed towards the surveillance and intervention of patients on long term opioid pain medication.

Observational databases linked to codified NOSQL datastores powered by high throughput phenotyping approaches are a useful mechanism for warehousing translational datasets such as EHR data including codified clinical notes and reports. This mechanism can be used to implement clinical decision support tools that would provide information tailored to specific patient needs. Prior studies in this area on monitoring post operative complications within electronic medical records and biosurveillance of influenza have established evidence for this method [11,12].

Further translational studies and implementation efforts are needed in the area of opioid prescribing and addiction in order to find a cost effective and quality intensive strategy for the nationwide opioid epidemic.

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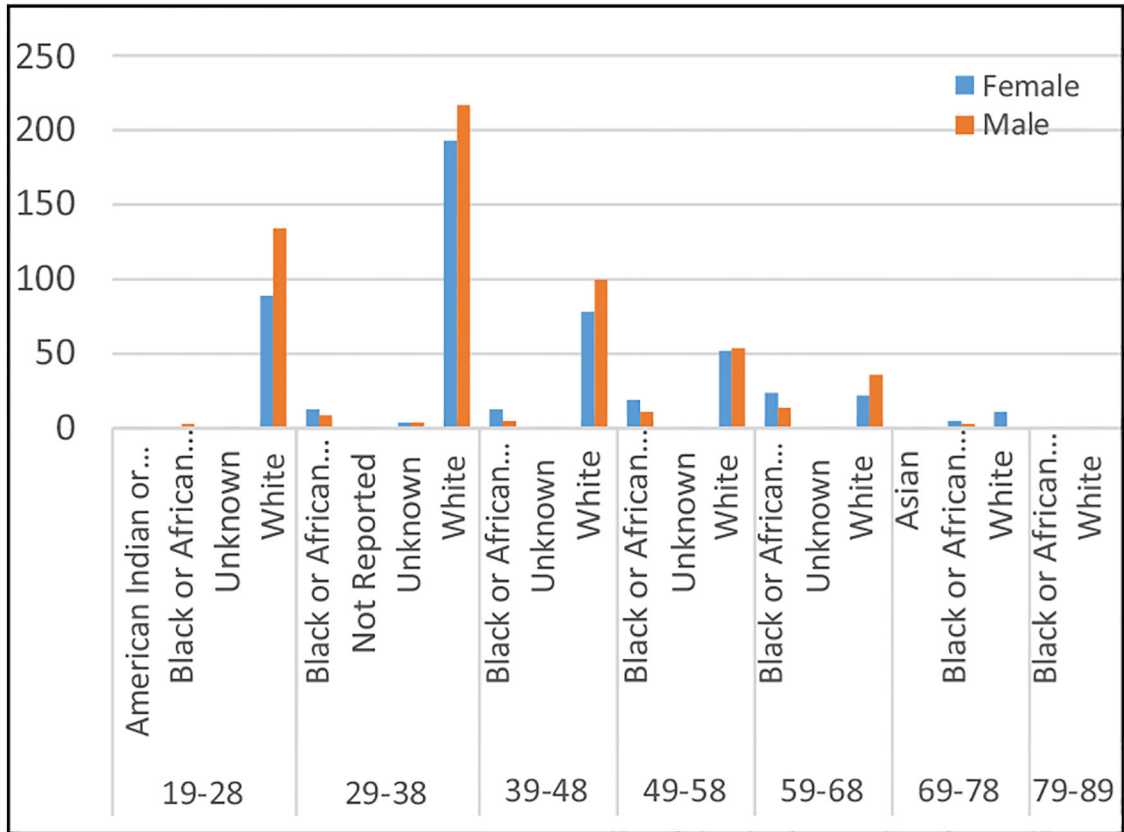
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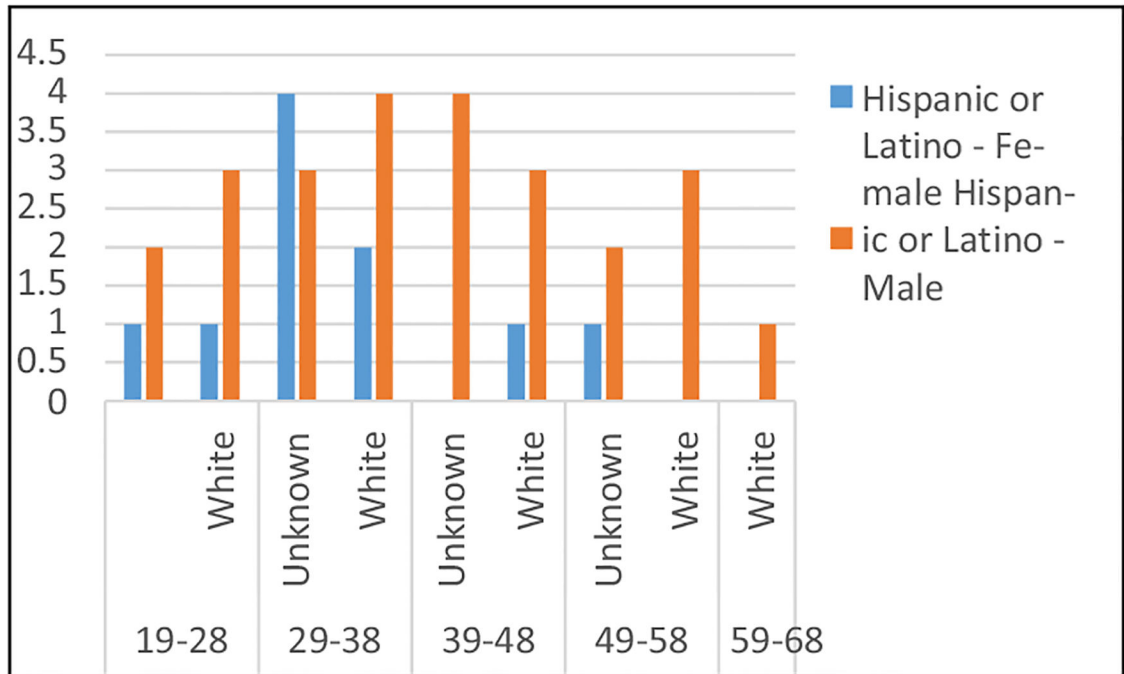
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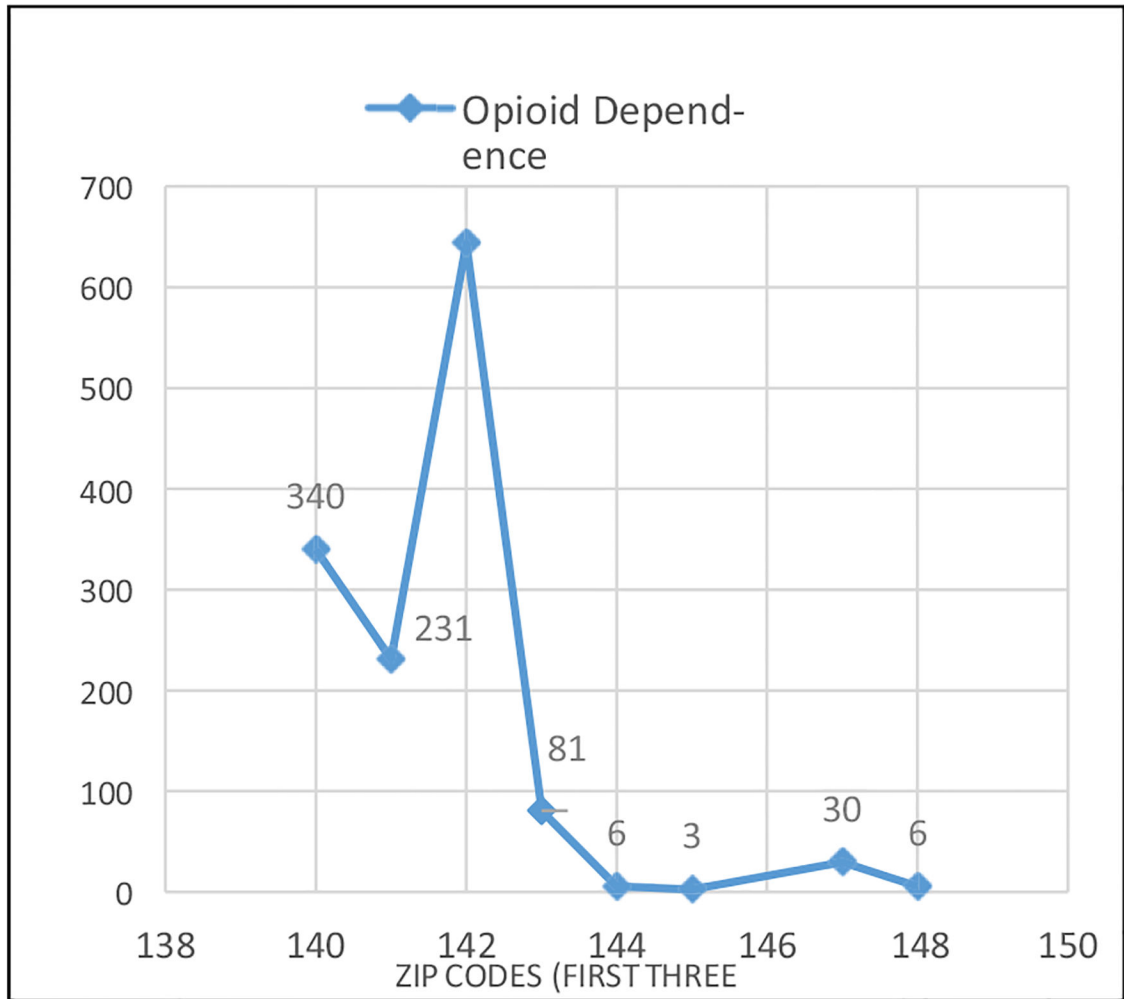


**Figure 1 –** Distribution of Opioid Dependence among the Non-Hispanic community in the clinic population of Western New York (x axis- age and ethnicity, y axis- number of people)





**Figure 2 –.** Distribution of Opioid Dependence among Hispanic population (x axis- age and ethnicity, y axis- number)



**Figure 3 -** Distribution of opioid dependent patients (y axis) according to first three numbers in zip codes (x axis)

**Table 1 -**

Age distribution of study population

Age Group (in years)	Opioid Dependent	Total population
19–28	279	36465
29–38	534	26313
39–48	236	25365
49–58	170	36270
59–68	106	36825
69–78	29	25313
79–89	2	25792
<b>Total</b>	1356	212343

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**Table 2 –**

Distribution of opioid dependence among Non Hispanic dependent population.

	Female	Male	Grand Total
<b>19–28</b>	<b>90</b>	<b>139</b>	<b>229</b>
American Indian/Alaska Native	1	1	2
African American		3	3
Unknown		1	1
White	89	134	223
<b>29–38</b>	<b>210</b>	<b>231</b>	<b>441</b>
African American	13	9	22
Not Reported		1	1
Unknown	4	4	8
White	193	217	410
<b>39–48</b>	<b>92</b>	<b>106</b>	<b>198</b>
African American	13	5	18
Unknown	1	1	2
White	78	100	178
<b>49–58</b>	<b>71</b>	<b>66</b>	<b>137</b>
African American	19	11	30
Unknown		1	1
White	52	54	106
<b>59–68</b>	<b>46</b>	<b>51</b>	<b>97</b>
African American	24	14	38
Unknown		1	1
White	22	36	58
<b>69–78</b>	<b>16</b>	<b>9</b>	<b>25</b>
Asian		1	1
African American	5	3	8
White	11	5	16
<b>79–89</b>	<b>1</b>	<b>1</b>	<b>2</b>
African American		1	1
White	1		1
<b>Grand Total</b>	<b>526</b>	<b>603</b>	<b>1129</b>

**Table 3 –**

Commonly written opioids

Medication	Quantity To Dispense	Activity Type Code	Medication Status	Provider number
Hydrocodone-Acetaminophen 7.5–500 MG/ 15ML SOLN	2250	Order	Active	168
Hydrocodone-Acetaminophen 7.5–325MG/ 15ML Oral Solution	1900	Order	Active	428728
Hydrocodone-Acetaminophen 7.5–325MG/ 15ML Oral Solution	1350	Order	Active	405425
Hydrocodone-Acetaminophen 7.5–500 MGTABS	540	Order	Active	387515
OxyCODONE HCl - 5 MG Oral Tablet	540	Order	Active	406621
Hydrocodone-Acetaminophen 7.5–500 MG/ 15ML SOLN	480	Order	Active	407834
Hydrocodone-Acetaminophen 7.5–325MG/ 15ML Oral Solution	450	Order	Active	405419
Tylenol with Co-deine #3 TABS	400	Order	Complete	177
Hydrocodone-Acetaminophen 10–325MG Oral Tablet	360	Order	Complete	406623
OxyCODONE HCl - 5 MG Oral Tablet	360	Order	Active	174