

Use of Data Science for Population Health Policy Analysis– The case of Opioid Crisis

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THESIS

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I dedicate this dissertation to my family and kids, without whom I would never have completed this degree.

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LIST OF ABBREVIATIONS

AHRQ	Agency for Healthcare Research and Quality
AI	Artificial Intelligence
AJPH	American Journal of Public Health
AMA	American Medical Association
ASAM	American Society of Addiction Medicine
BIDMC	Beth Israel Deaconess Medical Center
CDC	Center for Disease Control
CNS	Central nervous system
DEA	United States Drug Enforcement administration
DHHR	Department of Health and Human Resources
EMR	Electronic Medical Records
FDA	Food and drug administration
HHS	Health and Human Services
HRSA	Health Resources and Services Administration
ICD	International Statistical Classification of Diseases
JAMA	Journal of the American Medical Association
LEAD	Law Enforcement Assisted Division Program

LIST OF ABBREVIATIONS (*Continued*)

LOINC	Logical Observation Identifiers Names and Codes
MAT	Medication Assisted Treatment
ML	Machine learning
NAS	Neonatal abstinence syndrome
NBER	National Bureau of Economic Research
NIH	National Institute of Health
NIDA	National Institute of Drug Abuse
NOP	Non-opioid
NHCHC	National Health Care for Homeless Council
OIBD	Opioid induced bowel dysfunction
OJPHI	Online journal of Public Health informatics
ORADEs	Opioid related adverse drug events
PDMP	Prescription Drug Monitoring Program
SNOMED CT	Systematized Nomenclature of Medicine - Clinical Terms
WHO	World Health Organization

SUMMARY

A research of opioid crisis and related policies was carried out. This evidence-based research was aimed at investigating whether there is any convergence based on scientific evidence from literature and opinions of the patient population for opioid crisis.

Some of the suggestions include new policies for /to

- cancer patients
- other disease/disorders where the pain is high
- school /college going kids
- border security
- pharmaceutical marketing
- eliminate stigma
- physician training

I. INTRODUCTION

The Health and Human Services (HHS) Health Resources and Services Administration (HRSA) declared that the nation is amidst an unprecedented opioid epidemic (Health Resources and Services Administration, 2019) . The White house estimated that the opioid abuse costed the United states 504 billion in 2015 (Office of the President of United States, 2017). The misuse and abuse of this drug has allowed this public health problem to spiral out of control (Califf et al., 2016). According to CDC (Centers for Disease Control and Prevention), roughly hundred million people are suffering from acute and chronic pain in the US in 2016 (Dahlhamer et al., 2018). Opioids seem to remain a widely known class of medication in healthcare in the United States.

Health policy formulation in general has been based upon findings from the scientific literature, expert opinion and requests from the community. It is usually the case that patients, their relatives and caregivers directly know what is missing and what they actually may want in order to take care of the patients. It will be good for policy makers to include opinions and sentiments of community patients, caregivers, and family in the formulation of policy.

However, opioid policies are developed using scientific research. The assumption is that policies that take into account the opinions of the patients are more likely to develop policies that improve the health of patients based on the convergence of sentiments of patients and care givers and evidence-based research are more likely to be adopted by patients and communities. This research aims at investigating whether there is any convergence based on scientific evidence from literature and opinions of the patient population for opioid crisis

A. Background

The economic burden of opioid misuse in United States of America was \$78.5 billion by 2013 (Florence et al., 2013). The National Center for Health Statistics at CDC (Center for Disease Control) has estimated 130 deaths per day. In 1990s, Healthcare providers began to prescribe Opioid pain relievers at a greater rate when pharmaceutical companies reassured that patients would not become addicted (Health and Human Services, 2019). In recent decades, the US health care system has made several improvements in the Opioid policy. Numerous studies have explored prescribing as a causative factor (Dasgupta et al., 2018). Despite improvements in drug dosage, mortality outcomes continue to rise and the opioid epidemic has become the deadliest drug crisis in American history. Despite physicians training on opioid prescribing, pain management, much more is needed to end the opioid epidemic and AMA recommends evidence-based care for patients (American Medical Association, 2019). Despite increased attention to the issue, many questions remain in both creating and addressing this crisis (Zagorski, 2019) Overall, the rising rate of opioid addiction has spurred a many policy at the state and federal level. All states have created a prescription drug-monitoring program (PDMP). PDMP collects prescription data for controlled substances and facilitates detection of suspicious prescribing (Bhattacharya, 2017). Although drug supply is a key factor, there is association between quality of care, health outcomes (Dasgupta et al., 2018). According to Boston healthcare data and National Health Care for Homeless Council, lack of housing has been shown to negatively impact physical and behavioral health (National Health Care for the Homeless Council, 2016) among individuals experiencing homelessness (National Health Care for the Homeless Council, 2017). However, another study by National Bureau of Economic

Research (NBER) found out that improving economic conditions in distressed locations however is not likely to yield significant reductions in health outcomes (Ruhm, 2018)

It has been argued that further research on opioid data is critical to understand the opioid crisis. Therefore, I will be using data science tools such as machine learning (ML) and big data text analytics to understand different stakeholders' perspectives.

B. Where are machine learning, data science and big data used in public health

Data science field is comparatively new and most of the ML and big data used by health researchers fall in one of the five categories

(a) genomic or metabolic data (Stephens et al., 2015)

(b) geospatial data (Lee and Kang, 2015)

(c) clinical data collected administratively via electronic medical records (EMR) (Magnuson and Fu, 2014). This data is clinical decision support systems data. It is also called computerized physician order entry (CPOE) data.

(d) M-health (mobile health) and sensor data collected by a global positioning system (GPS) device or FitBit (Graham and Hipp, 2014).

(e) search term records (67), social media postings (Aramaki et al., 2011) or cell phone records (Aiello et al., 2016) which are highly unstructured (Wesolowski et al., 2015)

Each form of data has varied implications for research and practice i.e wider datasets normally require reducing the number of to least detentions as possible, which is done by

- selecting variables that are more important for further analysis (Alter, Brown, & Botstein,

2000)

- identifying variance patterns within the variables using methods such as principal component analysis (Titiunik, 2014)

Taller datasets require filtering out low quality observations reduce to information rich summary (Goldsmith et al., 2016).

A prominent application of artificial intelligence (AI) is machine learning (ML) and can transform health policy (Ashrafian and Darzi, 2018). Unsupervised learning has been used for spatial and spatiotemporal profiling, severe acute respiratory syndrome (Wang et al., 2006). K-means clustering was used to profile road accident hotspots (Anderson, 2009). Dengue fever surveillance and classification was used to express personal experience with dengue (Gomide et al., 2011). Text mining and clustering was used to identify depressed users (Yang and Mu, 2015).

Supervised learning has been used to predict transmission of tuberculosis from patient attributes (Mamiya et al., 2015). Classification was used to discover suicidal intentions (De Choudhary et al., 2017). ML methods have been used to identify important replicable predictors of subclinical coronary atherosclerosis (Sun et al., 2008). Fall classification was used on mobile phone data to detect injury to the elderly (Albert, Kording, Herrmann, & Jayaraman, 2012). Mortality risk score prediction in elderly population has been predicted using ML (Rose, 2013).

Semi – supervised learning has been used to build tool for adverse drug reactions. Social media data has been used for this purpose. Falls have been detected using semi-supervised learning from smartphone data (Fahmi et al., 2012). Semi-supervised modeling and clustering

have been used to detect atmospheric pollution in urban centers (Bougoudis et al., 2016). Semi supervised learning has been used to identify cancer subtypes (Koestler et al., 2015)

C. Statement of the problem

Most of substance abuse related causalities involve an opioid (Center for Disease Control, 2016). In 1990s, Healthcare providers began to prescribe Opioid pain relievers at a greater rate when pharmaceutical companies reassured that patients would not become addicted (Health and Human Services, 2019). Lack of knowledge by some pharmacists may have contributed to the failure of dispensing proper prescriptions for patients in pain (Joranson and Gilson, 2001). Opioids are used for treatment of injury, post-operative pain, cancer pain, acute and chronic non-cancer pain such as back pain or osteoarthritis (Johns Hopkins, 2017).

Between 1999 to 2010, opioid poisoning quadrupled, when the use of prescription opioids rose by 300 percent (Bhattacharya, 2017). Lack of self-control by individuals and the potential for abuse of medication contributed to the increasing of crisis (Upshur et al., 2006). Parallel to that, the widespread adoption of opioids was facilitated by marketing strategies. The strategies downplayed the very addictive capabilities of OxyContin's. Therefore, the primary care doctors, continued to prescribe the opioid pain relievers in many countries (Van Zee, 2009) (Wenghofer et al., 2011). Around the same time, opioids such as morphine and codeine, went through a similar unprecedented rise in production and sales (International Narcotics Control Board, 2019). Prescription opioids and increasing availability of heroin and illicit fentanyl, in spite of serious risks and the lack of proper evidence about their proper effectiveness long term have contributed to the biggest rates of overdose and opioid addiction in history of United States (Center for Disease Control, 2017). In response to the epidemic, the Centers for Disease

Control and Prevention (CDC) has released the “Guideline for Prescribing Opioids for Chronic Pain” in the month of March in 2016 (Center for Disease Control, 2016). Later, a number of states have introduced policies regarding limiting the prescribing of opioids, which align with what the CDC recommends. These policies limit the prescriptions between 3 – 14 days. In the year 2017, HHS declared that opioid crisis is a public health emergency and therefore announced a strategy (Health and Human Services, 2017) to combat the Opioid Crisis by a) Raising access to recovery and treatment services b) Encouraging use of opioid overdose reversing medications and drugs c) Boosting our understanding of the epidemic d) Supporting for innovative research e) Promoting better exercises for pain management. The Opioid Crisis Response Act of 2018 was passed to address the crisis (Senate Bill 2680, 2018)

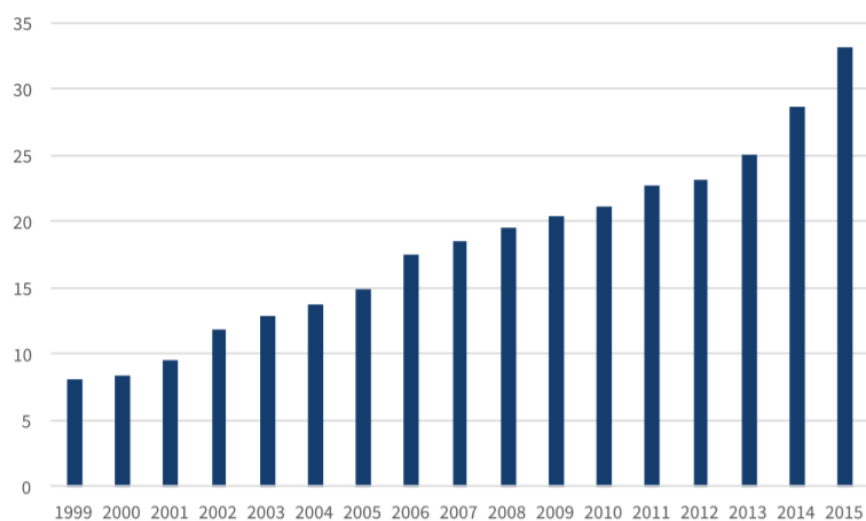
Although some policy steps such as Protecting Our Infants Act of 2015 (Senate Bill S.799, 2015) and the Comprehensive Addiction and Recover Act of 2016 (Public Law 114-198, 2016) have been taken, it is recommended that more work is required as opioid is a pediatric epidemic (Swartz, 2018).

Swartz et al. reported that

- A 2.95 kilograms baby who was born at 37-week gestation to a twenty year old woman with a previous history of use of intravenous heroin developed symptoms of neonatal abstinence syndrome (NAS).
- A 2-year-old girl developed acute encephalopathy caused by accidental buprenorphine ingestion and, as a result developed long-term morbidity and sequelae.

Consensus amongst researchers, policy makers and legislators is that opioid crisis is an epidemic. (Volkow et al, 2014)) (Manchikant et al.,2012)

Furthermore, Council of Economic Advisors suggests that these studies underestimate the problem by not valuing the most important fatalities resulting from the opioid overdoses. Figure below is from Council of Economic advisors.



Source: CDC Wonder database, multiple cause of death files

Figure 1: Opioid involved overdose deaths 1999-2015 CDC wonder

Protecting and improving the health of the population is public health. Public health surveillance is the exercise where agencies collect, interpret, analyze and manage the data in a systematic manner continuously, and circulating such data to programs that will facilitate by proper actions in healthcare (Thacker et al., 2012).

Health policy researchers for public health, health policy and public health surveillance have traditionally relied on sources other than the Internet to formulate evidence-based policies to address healthcare problems. According to Pew research center, 39% of Americans searched the Internet to address their personal health (Fox and Duggan, 2013). Internet data provides a global view of public health that is fundamentally different from disease reporting such as CDC reporting (Brownstein et al., 2008). Social media data helps researchers with real-time health data on a global scale and can be very important in healthcare research and public health crisis and surveillance. It is also suggested that the percentage of population using the Internet for health advice has been increasing and dramatic rethinking and other innovative strategies might be required for addressing the opioid crisis. Therefore, we will use data science on unstructured data from the internet.

D. Purpose

Most of the current policies are generated using clinical data. Clinical data can be categorized into the following major types: Electronic medical records, Administrative information, Claims data, Patient Disease registry data, survey data and Clinical trials data (University of Washington, 2018). Table I briefly explains these types of data. All that data does not contain many of the issues that people are discussing for incorporating in the Health policy. The data for the policies is typically either collected during an ongoing care or as part of a formal clinical trial for policy by the government. In tandem with government efforts, consensus amongst researchers, policy makers and legislators are that internet data / social media data can help in obtaining social and economic determinants to help opioid policy.

In this study, we firstly explore the literatures published from several journals on opioid research. This data is unstructured data.

Secondly, we will use big data source social media data to explore the real issues people are discussing. Over the past 15 years, micro-blogging in Twitter and short-message-service messaging have become integral to public health (Brownstein et al., 2009). Logs of users chosen keywords have been analyzed to provide data to yield important insights in current disease trends (Eysenbach, 2016)

TABLE I
TYPES OF DATA

#	Data	Medical facility	Type of Data
1	Electronic clinical data	Hospital data, clinical data	Data includes administrative data such as a) demographic information b) diagnosis and SNOMED codes, c) prescription drugs such as RxNorm codes c) laboratory tests and LOINC (Logical Observation Identifiers Names and codes) d) treatment e) physiologic monitoring data f) patient insurance data and billing codes such as International Classification of Diseases(ICD) -10 etc.
2	Administrative data	Hospital data	Data includes discharge data reported to government agency like Agency for Healthcare Research and Quality (AHRQ). Contains health statistics and data on hospital inpatient information and emergency department utilization
3	Claims data	Hospital data	It contains data on insured patients - inpatient/outpatient, pharmacy data, enrollment data, procedures, insurance claims between health insurance programs and health care providers.
4	Disease registries and clinical information systems data	National surveys, questionnaires	Clinical information systems data that track important information on certain chronic conditions such as diabetes, cancer, heart disease, asthma, alzheimer's disease

Techniques are available to extract information from social networks such as Facebook and LinkedIn etc., blogs and micro-blogs which include blogger, WordPress etc, Twitter, Tumblr etc, media sharing such as Instagram, Youtube etc, Wikis such as Wikipedia, Wikihow etc, social news such as Digg, Reddit etc, social bookmarking such as Delicious, StumbleUpon etc. Information can also be extracted from question-and-answer sites, review sites (Gandomi and Haider, 2011) (Barbier and Liu, 2011) .We will be using Twitter data to understand what people are discussing.

Furthermore, there has been no research combining both together the traditional science and science-based publication. This is the first research, which combines both traditional science and science-based publication approach with public opinion. This is achieved by applying ML techniques to address the opioid policy.

E. Research Questions

Given the above discussion the following research questions have been identified.

A. What does the current research in literature databases say on opioid?

A-1) Through a review of top health policy journal abstracts and a non-health policy journal abstracts identify what is the researchers' opinion on opioid.

B. How does data science and social media data contribute to population health policy?

B-1) Through extraction of issues on social media create data for analysis using data mining

B-2) Through application of natural language processing, ML algorithms extract features for population health policy

II. CONCEPTUAL DEFINITIONS

A. Machine learning

The computer science method of focusing and obtaining the most relevant information in a huge quantity of data is always important and with the increase in the Internet and World Wide Web (WWW) data, there are huge quantities of low-quality information (Blum and Langley, 1997) and problem of focusing on the most relevant features is very essential. An application of ML methods to huge datasets is called data mining (Alpaydin, 2010). An analogy is that of raw material where huge volume of raw material is extracted from earth and mined and processed leads to small precious materials, similar to data mining and machine learning. Machine Learning provides the basis for data mining and is used to extract information from the data that can be used for a variety of purposes (Witten et al., 2011)

Machine Learning techniques fit models algorithmically by adapting to patterns in data such as supervised learning, semi-supervised learning and unsupervised learning (Maglogiannis, 2007). In Supervised learning, we have the input variables and the output variable. This is called labeled data. If X is input variable and Y is output variable

$$Y = f(X)$$

It is called supervised learning, as it is similar to the process of teacher directing the learning process. The process of the algorithm learning from the dataset is similar to the process of student learning from a teacher where the teacher is directing the process. The algorithm makes predictions on the data and is checked for accuracy. Just as checked by the teacher and corrected. Learning is completed when desired level of performance is obtained. Supervised learning is classified into classification and regression (Murphy, 2012). Classification is used when the output variable y is a category, such as “disease” and “no disease”. Support vector

machines, random forest are examples of regression. (2) Regression is used when the output variable is a value, example “weight”. Linear regression and random forest are some algorithm examples.

Unsupervised learning is applied when we have no corresponding output variable and only have input data (X) (Hastie et al., 2001). To learn more about the data, we model the underlying structure in the data. These problems can be grouped into the following. (1) Clustering: Clustering is used to find groupings in the data such as grouping behavior of patients. Principal component analysis and K-means are some examples. (2) Association: Association is used to discover rules that describe large portions of the data. Example patients, who have disease X, also tend to have disease Y.

Semi- supervised learning, a sort of hybrid is where there is when huge amount of input data and only some amount of the data is labeled. (Hastie, 2001) where X is the input and Y is output variable.

B. Big data

Doug Laney in 2001 described the 3 Vs that make big data. They are data volume, data velocity, and data variety (Laney, 2001). Later IBM described big data as 4 Vs which are volume, variety, velocity and veracity (International Business Machines, Infographic: The Four V’s of Big Data, 2018). In healthcare, data is not created the same way and therefore data can be inappropriately labeled or applied (Magnuson and Fu, 2014) so value is the most important V. Veracity is the trustworthiness of the information. Velocity is the massive flow of data that is continuous (Health Data Archiver, 2018). Variety refers to the kind of data such as structured, unstructured and semi-structured. Table II below summarizes the size of data with examples.

TABLE II
SIZE OF DATA

Data Size	Equivalent
Bit	digit 1 or 0
1 Byte	8 bits = 1 character
1 KB (Kilobyte)	Short text paragraph of health data
4 Megabytes	Text storage per patient per year
10 Megabytes	Digital chest X-ray
80 Megabytes	Data generated per patient at BIDMC (Beth Israel Deaconess Medical Center)
1 Gigabyte	7 minutes of health HD Video
100 Gigabyte	Library floor of academic journals
122.3 GB	2016 PubMed baseline database
1 Terabyte	X-ray films in a large technological hospital Clinical text data (structured and unstructured at a large Hospital)
12 Terabytes	Twitter data per day
19 Terabytes	Images at a large hospital
400 Terabytes	National Climactic Data Center (NOAA) database
600 Terabytes	Facebook daily data
1.5 Petabytes	10 Billion photos produced on Facebook
20 Petabytes	Daily amount of storage produced by Google (2008)
8 Petabytes	All information available on the Web
150 Exabyte	Global size of data in healthcare as per IBM
1 yottabyte	Entire size of WWW

Majority of big data in healthcare is in the form of text and images and is unstructured. 80% of the world's healthcare data is unstructured (Health Data Archiver, 2018).

Twitter data produces data at an unprecedented scale with all 5 Vs in big data - volume, velocity, variety, veracity and value (Fan and Bifet, 2013).

C. Data Science

Broadly speaking, data science is a set of principles or algorithms used for extracting the information from data (Fawcett, 2013). Although the size of the data sets is huge, there is very little good quality and quantity of useful data. Therefore, the key word in data science is “science” (Leek, 2013). Data science is useful only when the data is used to answer the “science” part of data. While tools and technology are useful, the data is worthless if the right techniques are not applied to it or the data does not answer the question ML has been more broadly adopted within data science(Sun et al., 2008). Text Mining techniques are useful to extract information from unstructured textual data (Rajman and Besancon, 1998). Machine learning and text mining (essential as there is an explosion of text and unstructured data in health care systems) are at the core (Dhar, 2013)

Data mining and artificial intelligence can derive actionable insights from high dimensional, online, complex, heterogeneous and massive Twitter media data. (Aramaki, 2012) . Twitter community has been estimated to be of a size of 120 million across the worldwide in 2008, and more than 5.5 million messages are posted every day (O'Reilly et al., 2009). As of 2017, twitter had 330 M monthly users and its user base and data is increasing rapidly (Clement, 2019) with tweets of 500 M / day and approximately 200 billion / year (Internet Live stats, n.d.).

D. Natural language processing

Natural Language Programming works on manipulating natural language text/ speech to gather knowledge on how language is used and to perform desired tasks (Chowdhury, 2005). Some authors consider the use and study of NLP in medicine as one of the most challenging tasks in the field of medical and health information extration (Syns, 1996).

It is estimated that 80% of the world's internet data is in unstructured form (International Business Machines – The biggest data challenge, 2016). Data generated as we tweet, send Whatsapp messages, Facebook messages and Integram posts exists in the textual form, which is highly unstructured in nature. It is high dimensional data and the information present in it is not directly accessible unless it is processed. To obtain insights from text data, it is important to apply Natural Language Processing (NLP).

Several tasks can be performed in NLP and it is a systematic process for analyzing and understanding the information from the text data in an efficient manner. Quantitative approaches to automate language processing such as information theory, probabilistic modeling can be used (Manning and Schutz, 1999). N-grams are sequences of characters or words extracted from a text (Majumder and Mitra, 2002). N-gram systems usually use bigrams, trigrams and unigrams. Five-gram models can be produced but are not practical for very large corpus. N-grams are useful for many purposes. Creating N-grams allow for bringing syntactic knowledge into ML methods with additional natural language processing steps such as parsing for the construction such as stop words removal. Table III briefly shows examples of unigram, bigram, trigram to give a rough idea (Wikipedia, 2019)

TABLE III

Field	Unit	Sample	1-gram sequence	2-gram sequence	3-gram sequence
Sequencing of protein	amino acid	... dys-deu-der-drp, Cys, Leu, Ser, Trp,, dys- deu, deu- der, der- drp,, dys-deu-der, deu-der-drp, ...
Sequencing of DNA	base pair	...AGCTACGA...	T, A, C,, , TA, AC, CT,TAC,
Linguistics	character	...she_do_or_not_he_do...	...,s, h, e, _, d, o, _, o, r, _, n, o, t, _, s,h, e, _, d, o,she go, or not, she go...	..., she go or, not she go....
Linguistics	word	... he go or not he go, he, go, or, not, he, go,, he go, go or, or not, not he, he go,.	..., he go or, he or not, or not he, not he be, ...

EXAMPLE OF SEQUENCES

Let P be the probability of a word, then we can calculate the joint probability and the conditional probability of one word given its previous words (Jurafsky and Martin, 2019) and obtain N grams

$$P(s_1^n) = P(s_1)P\left(\frac{s_2}{s_1}\right)P\left(\frac{s_3}{s_1^2}\right) \dots \dots \dots P\left(\frac{s_n}{s_1^{n-1}}\right)$$

$$= \prod_{k=1}^n P(s_k / s_1^{k-1})$$

In this paper, NLP tasks such as Stemming, Lemmatization, tokenization, tf/idf, ngrams will be used for processing the text.

III. LITERATURE REVIEW

In this section, we will review some studies that attempted to address the opioid crisis. I performed an extensive literature on Google scholar and pubmed databases. Specifically, I searched for articles in JMIR and other health policy journals. Searches were referenced using keyword “opioid”, “opioid over prescription”, “opioid physician training”, “doctor shopping” etc. I independently screened the results for eligibility and reviewed the articles. I also examined websites of relevant government websites, expert’s opinion and included for additional review.

A. Studies on internet, Machine Learning and technology

To date there have been some studies that used Internet data for opioid crisis. We will discuss these studies below to for important concepts within these studies and to obtain a perspective that will form the basis of this study.

Internet data has been used for analysis of discussions on injecting and snorting and abuse of oxycontin (McNaughton et al.,2014). Internet data has been valuable for adults’ welcome threads discussions in opioid treatment accreditation course (Janssen et al., 2014).

Twitter data and unsupervised ML has been used for prescription misuse and sale of illicit opioids (Mackey et al., 2018). Crowd sourced data has been used to predict pharmacologic potency of opioid (Dasgupta et al., 2013). Social media data has been used to understand the relationship between images that misuse codeine, soda /alcohol glamorization, and integration with culture images (Cherian et al., 2018). It has been used to intervene on drug abuse problems (Kim et al., 2017). Social media form has been used to communicate on addiction with others and seek support and help (Lee and Cooper, 2019).

Cloud based apps and clinical workflows have helped in face to face time with patients which lead to improved opioid safety (Yoo et al., 2018). Blogging on chronic pain has been

shown to promote accountability and decrease isolation and has been helpful for opioid crisis (Ressler et al., 2012). Pain management apps seem to be liked by males than females with complex chronic pain problems (Rahman et. al., 2017). Multidimensional pain management app with data on pain intensity for cancer pain have led to significant patient outcomes (Agboola, et al., 2014) (Thurnheer et al, 2018)

User centered clinical decision support tool with regular feedback and updates to the tool has been a helpful web-based clinical decision tool for emergency departments initiation of buprenorphine for opioid use disorder (Ray, 2019) A rule-based clinical decision support system for complex symptom management was found useful (Lobach et al., 2016)

Wearable biosensors have been found helpful for real time detection of opioid and physiologic response to opioids may vary inversely with opioid tolerance (Carreiro et al., 2015) Digital pills have been used for real-time opioid abuse interventions to measure ingestion patterns (Chai et al., 2017). The pills consisted of a radiofrequency emitter in a gelatin capsule. This pill was encapsulated oxycodone tablet.

B. Studies on physician education

After examining opioid prescriptions and training, it is concluded that modifying physician education may be helpful (Schnell and Curry, 2018)

A study in US by Ingrid et al showed that there were substantial knowledge gaps between naloxone and prescription knowledge, barriers (logistical and attitudinal), facilitators, benefits. Some doctors expressed uncertainty about who to prescribe, fears on increased risk behaviors. offending patients, etc (Binswanger, 2015).

Another 2016 study showed that only 5 states require mandatory continuity education on pain management prescribing and only 1/2 of physicians obtain such training (Davis and Carr, 2016).

Federation of State Medical Boards (FSMB) distributed a guide “Responsible Opioid Use: A Physician's Guide”. A survey was sent to approximately 12666 licensed physicians and 508 physicians completed the survey and 80% agreed that the book is useful in Europe (Young et al., 2012)

A 2018 study by Molly et al! that used national data from 2006 to 2014 showed a link between medical school ranking and doctors’ characteristics to prescribing. It also showed general practitioners were more likely to prescribe than pain management specialists. It is possible that liberal prescribers impact the increase in use. Therefore, the study suggests training specific groups (Schnell and Currie, 2018)

Educational gaps exist among healthcare providers about prescribing among physicians (Hooten and Bruce, 2011). A 2019 study also advocates for pharmacist opinion on training and barriers to facilitate ways for increasing confidence in the dispensing of naloxone (Tanvee Thakur, 2019)

C. China’s lack of oversight on synthetic opioids and illegal drug supply names

The United States had the highest consumption of opioids (Humphreys, 2017). Since 1979, several US jurisdictions reported slow unintentional drug poisoning mortality rate. The rate however peaked at 18.1% from 1990 to 2002 and the number of opioid analgesic poisonings rose upto 91.2% (Paulozzi et al, 2006). Although it is argued that manufacturer Purdue pharma released OxyContin in 1996 opioid and therefore abuse increased (Van Zee, 2009) there is evidence that synthetic drugs have taken over the patients. Patients are prescribed pills, get them from family/friend and become dependent and switch to commercial alternative such as synthetic

drugs (Rinde, 2018). Synthetic drugs have taken over the market and continue to be an emerging evolving threat. China's lack of oversight has created exportation of synthetic opioids (Pardo, 2018) and significant quantities flow from China to Mexico, Canada.

Opioids bind the receptors in the spinal cord and the brain cord which disrupt the pain signals by releasing hormone dopamine activate the reward areas of the brain which creates a feeling of high or "euphoria". Opioids such as codeine, morphine are derived from plants naturally. Semi-synthetic opioids are manufactured in the lab such as hydrocodone (vicodin) and oxycodone (percocet). Fentanyl is a synthetic opioid which was developed for powerful anesthetic surgery, cancer etc. which is 100 times powerful than morphine and small dose can be dangerous. While in 2010, 14.3 % deaths were due to fentanyl, the figure increased to 59.8 % in 2017 (National Institute of Drug Abuse, 2019). Illegal fentanyl is fentanyl mixed with heroin & cocaine to increase the euphoric effect (Center for Disease Control, 2019). A study found that 86% had used nonmedical pain relievers were initiated through family, friends or personal prescriptions prior to using heroin (Lankenau et al., 2012). Fentanyl is the cause of several tragic incidents recently (The Economist, 2019) (Pediatric Academic Societies, 2019) (Whelan, 2019)

Studies show that drug-drug interaction when taken combined can be dangerous (Kotlinska-Lemieszek et al., 2015) (Jermaine D. Jones, 2012). Fentanyl tweets suggest that there are street and commercial names for opioid. Table IV briefly explains commercial and street names obtained from National Institute of Health (NIH).

Table IV

COMMERCIAL AND STREET NAMES OF OPIOID

#	Drug	Commercial name
1	Codeine	Captain Cody
2	Fentanyl, Sublimaze, Duragesic, Actiq	Apache, Tango and Cash, TNT, China Girl, Dance Fever, Friend, Goodfella, Jackpot, Murder 8
3	Hydrocodone	Vike, Watson-387
4	Hydromorphone,	D, Footballs, Juice, Smack,
5	Meperidine	Demmys
6	Methadone	Chocolate Chip Cookies
7	Morphine	Miss Emma
8	Oxycodone	Percs
9	Oxymorphone	Blue

By 2014, 10.3 million Americans were reporting the nonmedical use of prescription opioids (Substance Abuse and Mental Health Services, 2015). Opioids provide benefits to those who would misuse them beyond just getting high. Use of heroin has grown in response to control the supply of prescription opioid analgesics (Cicero and Ellis, 2017)

Street dealers might have set up illegal drugs for middle class white, non-hispanic people who have a predisposition to opiates (Harocopos et al., 2016). White males and females began opioid use with prescription drugs with adequate insurance, transitioned to street drugs. Whites and low academic achievers reported higher rates of opioid misuse (Lord et al., 2009)

D. Doctor shopping/Diversion, Prescription Drug Monitoring Program & Opioid misuse

Physicians are a key source for misuse for some adults (Schepis et al., 2018). Doctor shopping occurs when patients visit multiple physicians to gain surplus prescription of medication (Compton et al., 2015). Doctor hopping behavior where patients bypass nearby prescribers in favor of distant doctors and doctor shopping behavior both attribute to high-risk behaviors (Young et al., 2019)

To address doctor shopping this issue, PDMPs have been developed (Han et al., 2015). Prescription Drug Monitoring Program is an electronic database with prescription history of every patient that helps physicians to check for old and new prescriptions of the same drug. By 2012, PMDPs have been implemented in forty-nine out of fifty states in an attempt to reduce the mortality rate (Finley et al., 2017).

Although diversion control remains effective, there has been an increase in opioid related deaths and treatment admissions therefore additional public health measures are required (Simeone, 2017).

Additionally, Buprenorphine is a drug approved in many countries for the treatment of opioid dependence (Chua and Lee, 2006). However, since buprenorphine is most abused opioid in some countries, doctors prescribe suboxone (Simojoki et al., 2008) (Flinch et al., 2007). Suboxone is used to treat opioid addiction and Naloxone is used as a drug to reverse opioid overdose (Albert, 2019)

Prescription Drug Monitoring Program is useful as a screening tool and misses patients with other drug behaviors (Wilson et al., 2019). There is a serious concern that substitution has been occurred and people may have shifted to illicit drugs because of its relative availability and new interventions have to be implemented (Simeone, 2017).

Pharmacy and doctor shopping is a poor predictor of opioid abuse (Walker et al., 2019). Misusers of opioids were likely to have /be ($p < 0.001$) (Ives et al., 2006)

- previous drug or DUI conviction
- younger
- past alcohol abuse
- male

Additionally, misuse was facilitated by easy access via abuser's family friends or prescription (Lankanau et al., 2012). Misuse was also reported in adults who were uninsured or had behavioral health issues (Han et al., 2017)

There is also evidence that use of opioids before 12th grade in kids is associated with future use (Miech et al., 2015)

E. Drug Enforcement Administration (DEA) and reduction of opioid production

The United States Drug Enforcement administration recently is proposing to reduce the production of 5 opioids, which is a decrease of 53% of available production since 2016 (Drug Enforcement Administration, 2019).

- fentanyl - 31 %
- hydrocodone - 19 %
- hydromorphone - 25 %
- oxycodone - 9 %
- oxymorphone - 55 %

The quota set by DEA ensures patients have sufficient medicines and the United States. However, DEA is increasing the production of medical marijuana to help research and opioid epidemic. Marijuana to reduce the use of prescription opioids and such policy discussions would help (Wen and Hockenbery, 2018). Marijuana use among US pregnant women increased 3.9% in 2014 from 2.4% to in 2002(Jansson et al., 2018). Medical marijuana may not fix opioid crisis and may contribute to crisis (Finn, 2018)

F. Experts opinion to the extent of policy

Expert's opinion in medicine gives the readers an opportunity to look at key issues through the eyes of people who have authoritative knowledge (Walter and Hetzer, 2012). Therefore, in the section below, we will discuss expert's opinion in West Virginia and its primary recommendations. Next, we will discuss expert's opinion from American medical association and National Institute on Drug Abuse (NIDA)

1. Experts opinion from West Virginia

West Virginia suffers from the highest rate of overdose (Hedegaard et al., 2016) in the United States. This is also shown in figure 2. Prevention, early intervention, treatment, overdose reversal and support are part of the States' strategic plan (Health and Human Services, 2018)

The State department put together best practices reviewed by experts and set of high priority and short-term recommendations have been provided that are listed below. Table V briefly explains the West Virginia policy recommendations

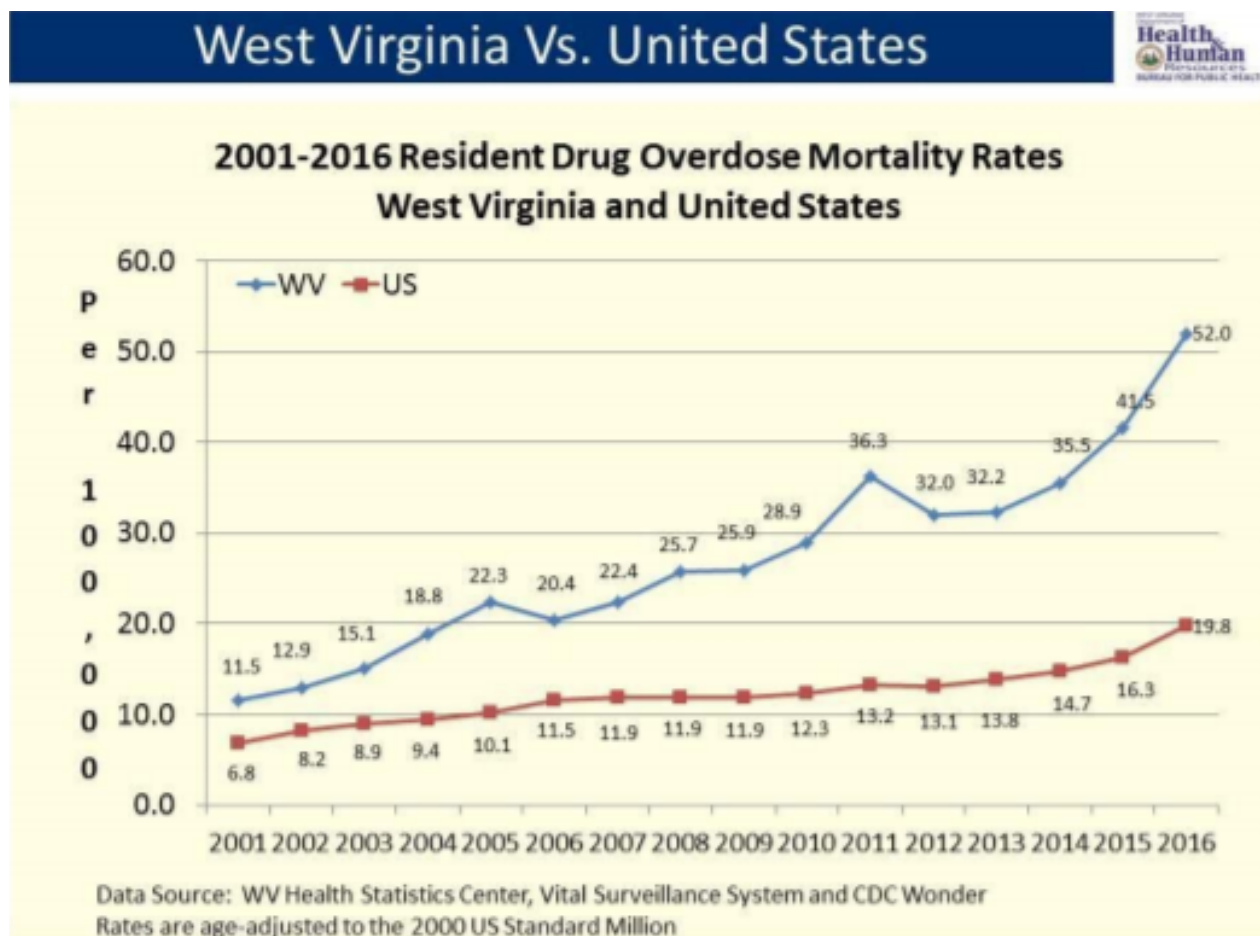


Figure 2: West Virginia opioid epidemic

Table V**WEST VIRGINIA POLICY RECOMMENDATIONS**

#	Priority	Recommendation
1	Prevention	1) Address inappropriate pain medication prescription by expanding the authority of medical professional boards and public health officials Key measures A) co-prescribing opioids and benzodiazepines. B) prescribing outside of the CDC guidelines
		2) Limit the duration opioid Key measure A) Check prescriptions time
2	Early Intervention	1) Develop a public education campaign that opioid addiction is treatable and address misinformation and associated stigma and support access to treatment through 1-844-HELP4WV. Key Measure A) Collect data before and after the education program and measure change in attitudes
		2) Expand law enforcement assisted diversion programs (LEAD) to help low level drug offenders experiencing a substance use disorder access treatment and support services Key Measure A) Obtain evidence of number of individuals diverted from jail to care.
		3) Remove legal barriers and strengthen lifesaving comprehensive harm reduction policies and programs based on scientific evidence Key Measure A) Remove legal barriers
3	Treatment	1) For effective treatment, remove regulatory barriers, require statewide quality strategy and have patients access to several options for opioid use disorder treatment Key measure A) Adoption of statewide quality strategy and removal of unnecessary regulatory barriers
		2) To reach people and to enter care, expand access to Key measure: Obtain and analyze the A) Number of patients participating in MAT, COAT (centered opioid addiction treatment) program B) Number of people in Emergency Departments

Table V**WEST VIRGINIA POLICY RECOMMENDATIONS (Continued)**

4	Overdose reversal	<p>1) Nalaxone is important for overdose reversal and therefore require all responders to carry naloxone. Support community-based naloxone programs</p> <p>Key measure: A) Obtain reports through EMS (emergency medical service) and poison control regarding overdose reversals</p>
		<p>2) For arranging outreach and other services notify the Bureau for Public Health of nonfatal overdoses</p> <p>Key Measure A) Obtain number of people who engage in care/recovery support</p>
5	Supporting families with substance use disorder	<p>1) For children born with NAS, expand such as Lily's Place.</p> <p>Key Measure A) Obtain data regarding out of home foster care placement</p>
		<p>2) Expand contraception and other contraceptive services f</p> <p>Key Measure A) Obtain data regarding infants with NAS</p>
6	Recovery	<p>1) Increase the number of peer based supports.</p> <p>Key measure A) Obtain coaches and peer-operated recovery residences</p>

2. Experts opinion from American medical association

American Medical Association (AMA) has set up task force to confront the opioid issue. Following recommendations have been made by AMA Chief Executive Officer, Steven Stack and Patrice Harris M.D., chair of the AMA's Taskforce (American Medical Association – End the epidemic, 2019). Table VI briefly explains the AMA policy recommendations

TABLE VI
AMA POLICY RECOMMENDATIONS

#	Experts recommendation for Physicians and Policy makers
1	encourage physicians to use state prescription drug monitoring programs.
2	enhance pain management training and education
3	increase access to substance abuse disorder treatment, particularly prescription medication abuse.
4	increase access to Naloxone, and consider co-prescribing Naloxone for patients at risk
5	safe storage and disposal of all medications
6	help end stigma
7	increase access to MAT
8	support access to mental health
9	remove administrative barriers
10	by increasing evidence-based treatment, support maternal and child health
11	support civil and criminal justice reforms

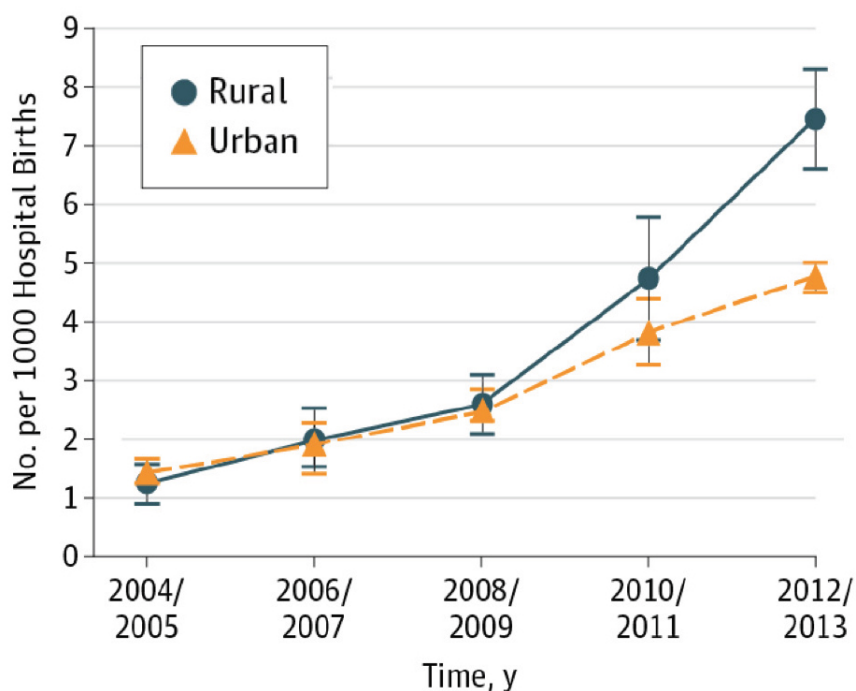
3. Experts opinion from National Institute of Drug Abuse

Below are policy briefs from NIDA.

a. Risks of opioid misuse during pregnancy

Between 2000-2012, NAS and opioid dependence on pregnant woman increased fivefold nationally (Epstein et al., 2013), (Patrick et al., 2015), (Tolia et al, 2015), (Patrick at al., 2012).

Figure 3 briefly explains the growing rate of NAS.



Rates of NAS are growing faster in rural areas

Figure 3: Differences in NAS and maternal opioid use in rural and urban areas

Use of buprenorphine and methadone has been recommended for effective treatment of opioid use disorder during pregnancy (Jones et al., 2010). Reducing medication dose is not recommended to prevent NAS (Kaltenbach et al., 1998). It has been shown that breastfeeding can reduce length of hospital stay (Klaman et al., 2017).

NIDA funded studies are trying for improving treatment strategies.

b. Opioid prescribers play a key role in stopping the opioid epidemic

Medical students and healthcare professionals receive only 9 hours of pain related training (Mezei and Murinson, 2011). It is also argued many are not trained to identify opioid addiction and therefore it is recommended that appropriate strategies be applied.

In Florida, PDMP use and policy changes have helped. Therefore, it is recommended that PDMPs can reduce opioid misuse and diversion (Delcher et al, 2015) (Brandeis University, 2016)

Below are CDC led effort recommendations to develop guidelines. Table VII briefly explains the CDC policy recommendations

TABLE VII
CDC POLICY RECOMMENDATIONS FOR OPIOID PRESCRIBING

#	Experts recommendation for Physicians
1	providers to authorize the lowest dose
2	providers to authorize no greater quantity than required for the duration of pain
3	for chronic pain, NOP therapies should be preferred
4	set up treatment goals therapy discontinuation, discuss risks and realistic benefits.
5	reassess risks and benefits throughout treatment
6	authorize immediate-release opioids
7	avoid increasing dosage to ≥ 90 MME per day reconsider when increasing dosage
8	determine benefits and risks between one to four weeks of starting the therapy for chronic pain
9	use a validated screening tool to find out about substance abuse
10	use PDMPs to check concurrent use
11	use urine drug test screening
12	avoid opioids and benzodiazepines together
13	provide evidence-based treatment for opioid use disorders

c. Naloxone as a lifesaving science for opioid overdose

Between 1996 to 2014, use of naloxone reversed 26,500 opioid cases (Center for Disease Control, 2014) In Massachusetts, Naloxone distribution program reduced opioid overdose deaths by 11 percent in nineteen communities (Eliza Wheeler, 2015). No evidence of adverse reactions has been reported by naloxone (Wermeling, 2015).

National Institute of Drug Abuse funded research developed the first Food and Drug Administration (FDA) approved naloxone nasal spray—NARCAN. Other solutions include reaching communities in need and improving public health by evidence-based prevention and treatment interventions

d. Effective treatment for opioid addiction

According to World Health Organization (WHO), buprenorphine, methadone, and naltrexone are effective for the treatment of opioid disorders (World Health Organization, 2004). Medication Assisted Treatment (MAT), decreases opioid problems and infectious disease spread (Mattick et al.,2009) (Mattick et al.,2003) (Schwartz et al., 2013). Patients taking medication were more likely to be in treatment therapy than patients that did not include medication (Mattick et al.,2003), (Mattick et al.,2009). Medication Assisted Treatment reduces symptoms of NAS and duration of hospital stay (American College of Obstetricians and Gynecologists, 2017).

In 2017, U.S. Food and Drug Administration approved Sublocade buprenorphine injection. Sublocade in addition to Probuphine, improves treatment retention. It is suggested that people who initiate MAT in the ED (emergency department) are keener to remain in treatment (D'Onofrio, 2015) and therefore reaching out to patients not initiated in MAT in ED is essential. Naltrexone reduces relapse rates among adults with a history of opioid use disorder (Hastie, 2001). The United States does not have sufficient treatment capacity to provide MAT to all

patients with an opioid use disorder (Jones et al., 2015). Medicated- Assisted Treatment is offered by half of privately-funded substance use disorder treatment programs and 1/3rd patients with opioid use disorder receive it (Knudsen et al., 2011). Therefore, medication use should be widely promoted.

4. Experts opinion from Substance Abuse and Mental Health Services Administration

From 2012 to 2014, SAMHSA included 1) panel members 2) federal staff 3) state agency staff and came up with guidelines entitled '*Federal Guidelines for Opioid Treatment Programs*' (Substance Abuse and Mental Health Services Administration, 2015)

a. Telemedicine

Telemedicine services are helpful and so are interactive audio and video telecommunications systems for real-time communication

b. Administrative organization

Roles and responsibilities should be designated. Roles and responsibilities ensure quality patient care and should meet the requirements of all regulations

c. Facility management

Programs should have enough space and adequate equipment and there should be proper facility management

d. Medication unit

Programs should establish a medication unit to administer medication therapy.

e. Human resource management

Acceptable number of resources should be employed as well as should trained including physicians and nurses.

g. Risk management

Appropriate risk management Programs must be developed and maintained for effective policies and procedures

h. Continuous quality improvement

Programs must maintain current quality continuously with best practice approach

G. Hypothesis

Despite improvement in policies using traditional data sources, opioid addiction remains a long-lasting problem that can cause health, economic and social problems. Hence, there may be a divergence between evidence-based policies derived from the scientific literature and the needs of the community as expressed in social media sites. That is, the science-based policies may not be addressing the needs and desires of the opioid community. Therefore, the data should include nontraditional unstructured data that is the social media data apart from traditional data to develop policies. Twitter data produces data at an unprecedented scale with all 5 Vs in big data - volume, velocity, variety, veracity and value (Fan and Bifet, 2013). Twitter data offers an opportunity to understand what people are discussing which is essential for Public health policy

H_0 1: There is no convergence between policies formulated for opioid control based on scientific publications and expert opinions and the needs of the opioid community

H_1 1: There is convergence between policies formulated for opioid control and the needs of the community.

IV. DATA SOURCES AND METHODOLOGY

A. Data from literature sources

The dataset contains abstracts from 8 health policy journals and 3-year research articles from PubMed. The 9 journals are OJPHI (Online journal of Public Health informatics), Health affairs, Health Economics (Wiley online library), JAMA (Journal of the American Medical Association), Annals review, AJPH (American Journal of Public Health), NIH

B. Data from social media Twitter

Twitter data was collected in March 2019. This period was selected to obtain the most recent public opinions in the country. Hashtags (search terms) have been developed to identify the tweets related to opioid after consulting a physician and commissioner. The initial search terms included common terms as well as drug specific. Table VIII shows the hashtags used

TABLE VIII
HASHTAGS FOR DATA ACQUISITION 1

Hashtags included
Opioid policy
Opioid crisis
Fentanyl.
Codeine
Hydrocodone
Morphine
NAS
Neonatal Abstinence syndrome

C. Methodology

1. Processing steps from literature data

The NLP article pre-processing steps are tokenization, ngrams (1,1), ngrams (1,2), ngrams(1,3) and stop words removal (Figure 1). I fit ML algorithms (Multinomial Regression, Random Forest, Support Vector Machine (SVM), Naïve bayes) to the training documents and get predictions for the test documents. I compare different algorithms: Multinomial regression, Naïve Bayes, SVM and Random forest. Subsequently, features from the best performing algorithm were retrieved for each class.

The preprocessing steps are given in Figure 4.

2. Processing steps from Twitter data

Web-based methods are classified into two types:

- (1) search based (Eysenbach, 2006) (Polygreen et al., 2008), (Hulth et al., 2009) (Ginsberg et al., 2009). The search based approach assumes that the number of related queries correlate to patients.
- (2) micro blogging based (Zhao and Rosso, 2009). Here it is said that related post reflects the epidemics. Twitter data is an example of micro blogging-based approach.

A series of steps are shown in Figure for creating the datasets. The flowchart for extracting Twitter information is given in Figure 5.

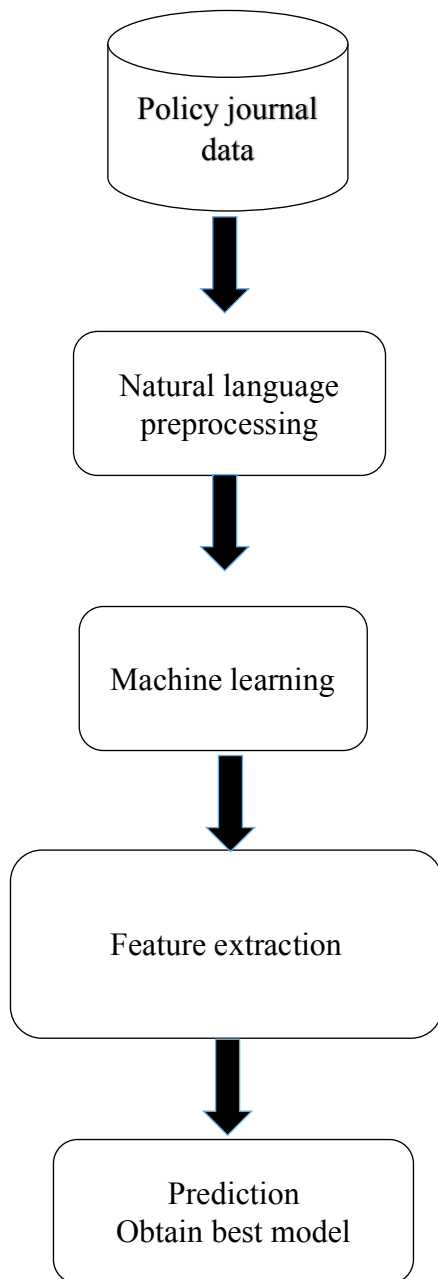


Figure 4: Methodology to investigate on several journals

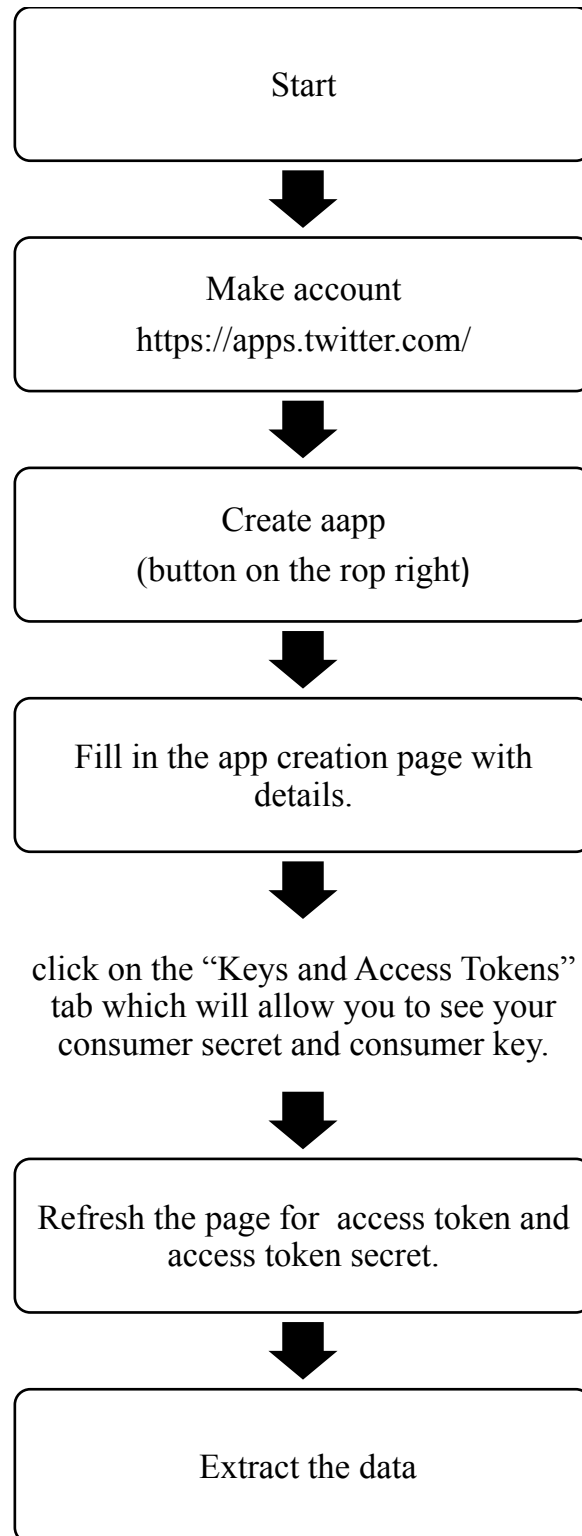


Figure 5: Flowchart of Twitter data extraction

The flow chart for applying ML is below

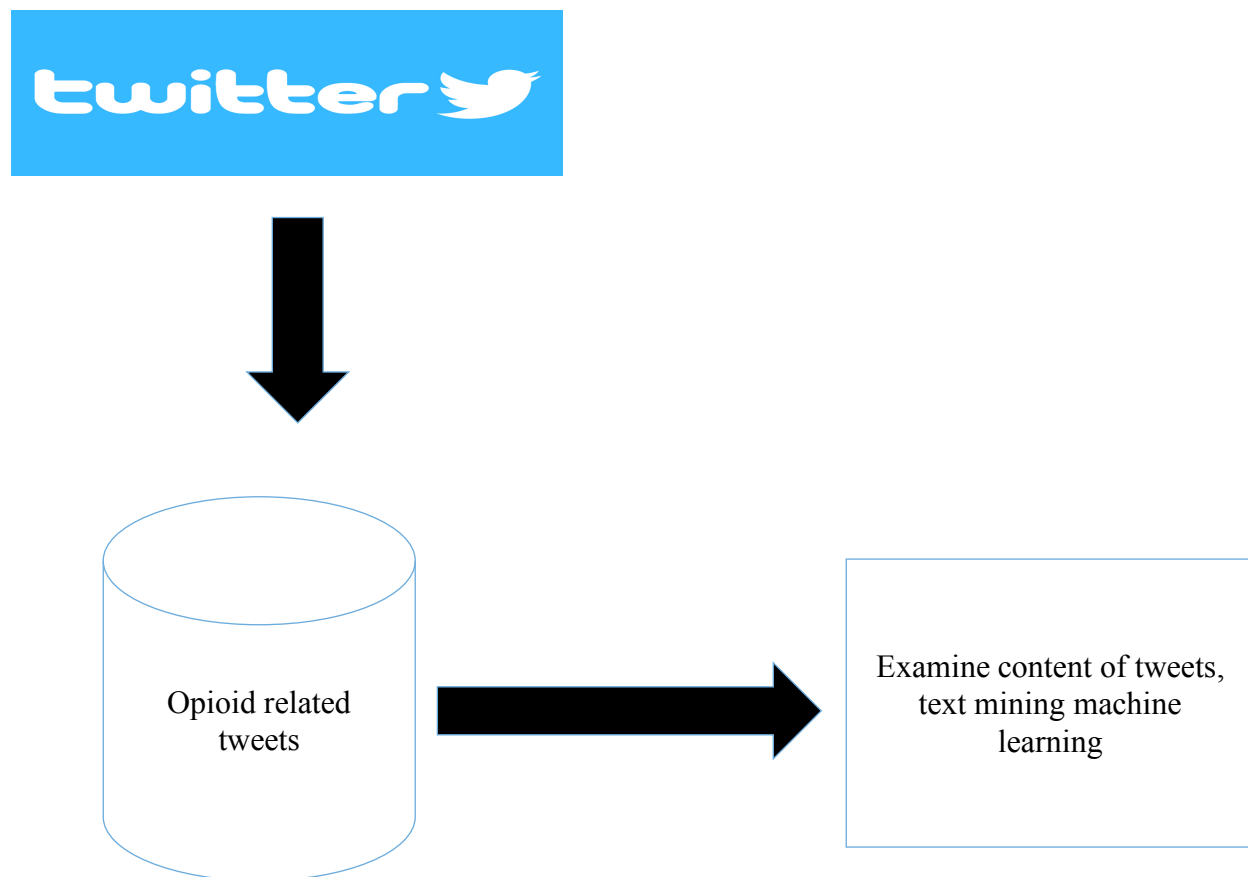


Figure 6: Downloading data for text mining process

a. Data acquisition and curation

The sample fictional data obtained in Json format is shown below. Some data has been deleted and actual data is a lot messy. The data is obtained at very frequent intervals.

```

"created_at": "Thu Mar 31 09:09:17 +0000 2011", "favourites_count": 472, "utc_offset":
-25200, "time_zone": "Pacific Time (US & Canada)", "geo_enabled": false, "verified":
created_at": "Thu Mar 31 09:09:17 +0000 2011", "favourites_count": 472, "utc_offset": -
25200, "time_zone": "Pacific Time (US & Canada)", "geo_enabled": false, "verified
....

....

3188728095/6a176e554d9eeda551c0c38bc5fd09a4_normal.png", "profile_banner_url":
"https://pbs.twimg.com/profile_banners/274930264/1486786822", "profile_link_color": "

created_at": "Thu Mar 31 09:09:18 +0000 2011", "favourites_count": 472, "utc_offset": -
25200, "time_zone": "Pacific Time (US & Canada)", "geo_enabled": false, "verified

created_at": "Thu Mar 31 09:09:19 +0000 2011", "favourites_count": 472, "utc_offset": -
25200, "time_zone": "Pacific Time (US & Canada)", "geo_enabled": false, "verified

created_at": "Thu Mar 31 09:09:20 +0000 2011", "favourites_count": 472, "utc_offset": -
25200, "time_zone": "Pacific Time (US & Canada)", "geo_enabled": false, "verified

, "time_zone": "Pacific Time (US & Canada)", "geo_enabled": false, "verified}

```

The above data has been cleaned. Table IX explain the sample messy data that is cleaned again to improve the quality of data.

TABLE IX
MESSY DATA

b'RT @CTVAAtlantic: Public health officials warning of powerful new opioid now in N.B. https://t.co/2pcSrUQfc6 https://t.co/7KdNO99qYq '
b'RT @DanGraur: ~64,000 Americans died from opioid overdoses in 2016 because their breathing shut down. Opioid binding to \u03bc-opioid receptors\u2026'
b'Knock Out Opioid Abuse Town Hall Brings Opioid Discussion to Union County https://t.co/zFKCNsOCQ2 https://t.co/coQT9dlNaY '
b'Office-based Treatment of Opioid Dependence https://t.co/mFcUm8u9Y5 '
b"RT @LynnRWebsterMD: Babies cannot be born addicted. Please don't label them. https://t.co/hSRCfwjuo3 "
b"RT @CNNPolitics: There are 28 concurrent active national emergencies. The opioid crisis didn't make the list https://t.co/vIbicuAmF3 https://t.co/vIbicuAmF3 "
b'How the Opioid Epidemic Affects Women: Bridging the Gender Gap https://t.co/BOFvSYQgto '
b'RT @katiewr31413491: Like opioid effect when many ASD kids drink cow\u2019s milk https://t.co/iqC6dHTv1d '
b"RT @CNNPolitics: There are 28 concurrent active national emergencies. The opioid crisis didn't make the list https://t.co/vIbicuAmF3 https://t.co/vIbicuAmF3 "

This data is further cleaned to obtain opinions. The data sets contain only relevant information after cleaning. Table X explains the clean data

TABLE X
CLEANED DATA

Public health officials warning of powerful new opioid now in N.B
64,000 Americans died from opioid overdoses in 2016 because their breathing shut down.
Knock Out Opioid Abuse Town Hall Brings Opioid Discussion to Union County
Office-based Treatment of Opioid Dependence
Babies cannot be born addicted. Please don't label them.

V. STUDY RESULTS AND DATA ANALYSIS

A. Analysis of literature sources

The Multinomial logistic regression model with ngrams (1,3) outperformed the other approaches (Table 11). The model has a 0.75 % F1-score, followed by SVM with accuracy 0.73%, naïve bayes with 0.62%, random forest with 0.52 %.

Appendix contains the features and discussions for each class. Table XI explains the results of literature sources

TABLE XI
RESULTS USING DIFFERENT ALGORITHMS 1

	multinomial regression algorithm	svm	random forest algorithm	Naive bayes algorithm
precision	0.75	0.71	0.42	0.57
recall	0.77	0.73	0.52	0.62
F1-score	0.75	0.71	0.40	0.55
accuracy	0.78	0.73	0.52	0.62

B. Analysis of social media data

A total of 45623 tweets were downloaded from Twitter. Appendix I contains discussions and features

VI. DISCUSSION

The use of data science on researchers work and community opinion on Twitter is an innovative approach and to our understanding this study is the first kind in its type. The study focused on comprehensive research on current opioid policies.

Through the initial phases of the study, researchers' opinion and expert's opinion was analyzed for previous attempts and insights, and to create a reliable link that connects expert's current policies in the hardest hit states.

Unstructured data was collected from literature sources and social media and analyzed. Major findings of the study include stringent border security policies, new policies for cancer patients for patient satisfaction, application of school-based policies on opioid, policies for pharmaceutical companies, policies to eliminate stigma and physician training.

Although DEA is reducing the production of opioid and increasing the production of medical marijuana for cancer patients, the solution may not help non-cancer addicts. The problem is not with medical opioid but illegal opioid.

The needs of the community are not fully met at this time.

VII. CONVERGING OPINION

Here, I briefly present some opinions and public health response as well as converging opinion.

Experts and public agree on stigma associated with opioid crisis. Government may need to provide guidance and policies to recognize stigma in everyday behavior.

Researchers and public opinion agree on increasing the border security policy to cut drug trafficking. Researchers opinion is that there is no appropriate physician training

Public opinion is that new opioid policies have not helped cancer and postsurgical patients as they are without painkillers. Experts agree that further physician training is required.

A deeper understanding of public opinion shows that school psychologists, social workers, counselors and school based mental health should be applied. Educational efforts do work and the case for cessation of opioid use is as compelling as that of cigarette smoking, teen pregnancy, alcohol related harms, heart disease and stroke, nutrition and micronutrient deficiencies, under nutrition and obesity.

VIII. POLICY RECOMMENDATIONS

A. Policies for cancer patients

In the early days of the crisis, officials had reasons to blame on the dosage as people died unexpectedly on drug overdose. For drugs/medicines, the aspect most subject to regulatory intervention is prescription. Therefore, the government tightened controls on doctor's prescription. Although overdose deaths declined policy makers may have misjudged the addictive potential of the drugs and the risks it posed to an average patient and missed to focus on those most vulnerable to addiction – opioid abusers who are most vulnerable to addiction and not cancer patients.

1. Current policies have left some cancer patients without painkillers and some patients are not satisfied. Since patient satisfaction is an indicator for measuring quality of life and since the pain threshold for every patient is different, cancer patients should have a say on medication restriction and new policies for cancer pain should be formulated.

B. Policies for other diseases/disorders that may need more pain relievers

Some diseases/disorders may need more opioid dose.

1. Questionnaires that are subjective / objective should be developed to identify those who need to receive loading dose or maintenance dose, up titration or down titration.

Continuous monitoring of the levels of different types of opioid should be performed to minimize overuse and complications associated with it.

C. Policies for students, school and college going children

White, non-hispanic kids may get addicted on opioids after a dental surgeon gave him percocets or vicodins. Some kids obtain pain relievers from relatives or friends or buy illegal pills from a dealer.

1. Opioid use has to be restricted to only those for whom there is a genuine need. A careful evaluation of pain symptoms and need for opioids need to be done prior to administration
2. Policies on therapy for students, school and college going children should be implemented. America is racially and ethnically diverse. Since a social worker ensures a healthy living situation by considering several variables, a social worker may determine at-risk populations and design and implement programs to educate students, school staff, and parents.

D. Policies for Border Security

Some people turn to ‘doctor shopping’ by seeking prescriptions from multiple physicians and by using illegally made non-pharmaceutical fentanyl (which mixed with heroin and cocaine and a gram can kill 500 people) at the same time. To solve this problem, CDC urged to expand the use of naloxone, conduct trainings on naloxone administration, detect drug overdose outbreak, screen for fentanyl. E-prescribing may help in prescription misuse and track for compliance.

1. It is hinted that drug traffickers either directly ship to United States via international mail or into Mexico to enter into the United states. Adulterated fentanyl from Mexico enters United States through the Mexican border. Border security might be a needle-in-a-

haystack problem however better policies and strategies are required. Therefore, Border security is important and stringent policies and research will help prevent further crisis.

F. Policies to eliminate stigma

Opioid use is generally viewed as a moral failing. However, opioid use disorder is like a disease

1. Government may need to provide guidance and policies to recognize stigma in everyday behavior.

G. Policies for pharmaceutical companies & its sales representatives on opioid marketing

Opioid settlements have been compared to Tobacco settlements (between the State and companies Philip Morris, Reynolds, Brown and Williamson and Lorillard) in 1998. Lawyers have argued that companies like Purdue Pharma, Teva Pharma, Johnson and Johnson have ignored red flags and marketed opioid use.

1. In order to be successful long term, pharmaceutical companies need to stop aggressive marketing, as there is a risk of lawsuits and bankruptcy. The problem cannot be addressed by reducing the number of sales representatives. Appropriate training should be provided to marketing and sales representatives on the dangers of opioid with examples of evidence such as patients ‘passed out in the waiting room’ or things that would indicate a ‘pill mill’.

H. Policy for Physician training

Since hospitals/practices may vary, characteristics of patients may be different, continuous training is essential for Physicians.

1. Most physicians are competent after the initial 8 hours of training. However, after the initial training of sabaxone/ buprenorphine, which is generally ASAM (American Society of Addiction Medicine) approved, there is no recertification at the end of 5 years. Therefore, there should be policies for physicians to get recertified.

IX. LIMITATIONS

The study covers a large breadth of knowledge related to opioid from various journals.

The first limitation in this study is that it does not cover all the journals due to limitations of time and resource constraints. Therefore, incidence and prevalence may vary.

The study used Twitter data to understand public opinion. The second limitation is that it covers latest public opinion. As this study is attempting to build the foundation for obtaining public opinion from Twitter, it may be beneficial to obtain additional data with additional hashtags in future.

Thirdly, not all the people are on social media for their opinion therefore, this may introduce bias in the study.

Additionally, the study did not use data from other social media such as Instagram, Facebook etc. Sources of data not obtained could influence comparison and there may be convergence that I may not have explained.

Finally, there are several modalities of pain management. Analgesics include nerve pain medications, antidepressants, anti-inflammatory analgesics and opioids. For nerve blocks and pain, tens unit, an electrical simulation can be used for nerve stimulation. There are several pain management modalities for muscle and bone in cancer. Studies have shown that Magnesium is safe for treatment of non-cancer pain (Park et al., 2019) and Intranasal ketamine may be utilized for pain control in cancer patients (Shteamer et al., 2019). Therefore, additional research can be conducted on other sources of pain treatment for different kinds of pain.

APPENDICES

Appendix A

Some discussions based on the features from Wiley Health are below

- Doctor shopping laws in addition to prescription laws reduce prescription opioid treatment admissions (Popovici et al., 2018) (Ioana Popovici, 2018). Availability of prescription may threaten sellers and force alternative methods to increase profit margins (Hempstead and Yildirim, 2014). Access to Health Insurance and affordable care act declined the treatment of substance use disorder of dependent care by 11%. Illegal drug markets demand and the use of stimulants apart from opioids known as ‘uppers’ such as methamphetamine, has been increasing behind the scenes (Cunningham and Finley, 2015)

Some Features from Wiley health are below

Effectiveness

admissions

laws

incentives

doctor shopping laws

measures effectiveness

illegal drug

treatment quantity access

drug prices

pain management clinic

dependent coverage

payment source

Illegal drug markets

Appendix B

Some discussions based on the features from OJPHI

- Systematic syndromic surveillance is useful for detecting crisis in public health; the data is obtained from research articles and Internet. Abstracts on the surveillance of opioid abuse can be used for disease surveillance (Dixon, 2017). Multidimensional Tensor Scan for can be used for opioid overdose surveillance (Neill, 2017)
- To enhance opioid overdose surveillance, case definitions with free text fields from ambulatory system data can create analytical datasets that can be used to define opioid epidemic. The case definitions useful are “drug abuse”, “drug use”, “poisoning”, “drug ingestion”, and “overdose”, narcan (Bergeron et al., 2018).
- People with private insurance are rated with higher rates of opioid use, hospital charges were impacted by previous comorbid factors such as mental health, males are more likely to be hospitalized than females, white population are more likely to be admitted than other ethnic racial groups (Sundaram-Stukel et al, 2017).
- A study on prescription drug surveillance showed that Kansas male patients between 45 to 54 years of age had the longest history of opioid overdose. Syndromic surveillance data from Utah showed that the highest rate of opioid-overdose visits occurred among females and between 18 to 24 of age. Data from Emergency Medical Services (EMS) records or ICD-10 hospital diagnostic codes can provide good surveillance case definition. Terms included were main diagnosis terms related to opioids, unspecified overdose, narcotics, and narcan or naloxone. Terms excluded were suicide, alcohol overdose, withdrawal, detoxification, rehab, addiction, constipation, chronic pain.
- Philadelphia focused on recovery-oriented approach to treatment, however this approach is not sufficient for preventing subsequent fatal overdose (Pizzicato et al., 2018)).
- Methadone death and incident review act of October 2012 increased the state oversight and therefore resulted in reduced overdose of methadone and Xanax

Some features from OJPHI are below

surveillance	free text	charges introduces selection	Use
data	charges associated	charges realized patient	Emergency department
syndromic surveillance	hospital charges associated	Overdose	Virginia
urls	affect hospital charges	female patients white	Operative recovery hospitals
definitions	charges assess	Kansas	Groups ICD 10
hospital charges	charges assess costs	Utah	Canada critical
multidimensional	charges associated	Ambulance	Combinations of
tensor	hospitalization		methadone xanax
charges	charges introduces		

Appendix C

Some discussions from Pubmed are below

Opioid prescription is the chief driver of opioid use after (Kuo, et al., 2019)

- (Alfred C. Kuo, 2019). Patients who used opioid prior find it difficult to manage postoperatively with opioid (Wong and Goyal, 2019).
- Fentanyl abuse is a public health issue and pharmacovigilance systems reporting should be considered (Schifano et al., 2019)
- Opioid overdose patients may benefit from being treated with both substance use and depression as symptom of depression significantly predicted frequency of substance use (Anand et al., 2019)
- Buprenorphine/naloxone and MMT (methadone maintenance treatment) are associated with reduced opioid related mortality (Laroche et al., 2018).
- New molecular entity, full mu-opioid receptor agonist with a slow rate of CNS (central nervous system activity) has been designed to provide analgesia while reducing abuse. changes in cortex area of brain may result in cognitive impairment. (Bazov et al., 2018)
- Can be administered to obese and diabetic patients and no change in dosage (Porazka et al., 2019)
- Literature from research provided evidence that rural US communities suffer from misuse of opioids compared to urban or metropolitan areas (Palombi et al., 2018)
- Opiate use during pregnancy has been increasing making it an important social concern and commonly prescribed opiates cause neonatal abstinence syndrome (Martins et al., 2019). Opioid-induced bowel dysfunction (OIBD) is common among patients and early multidisciplinary approach is necessary.
- Features such as kratom, loperamide and other medicines indicate discussions on alternative treatments for opioid use recovery. FDA warns consumers not to use Kratom (Food and Drug Administration, FDA and Kratom, 2019)

Some features from pubmed

surgery	naloxone	Literature	Research	Kratom
management	therapy	molecular	Alcohol	loperamide
receptors	depression	education	Brain	
clinical	buprenorphine	weight	Cancer	
administration	pain	long term	Pregnancy	
	management	providers		
fentanyl	quality evidence	opioid receptors	Constipation	

Appendix D

Some discussions from health and medical informatics are below

- Males and females exhibit sex specific changes in brain metabolism and they respond to treatment differently. Hence, sex specific treatments should be applied and therefore such policies should be applied (Santaro et al., 2017).
- Shared medical appointments (SUD) and group therapy are effective, evidence-based treatment for Opioid epidemic (Daum et al, 2017).
- Delayed Posthypoxic Leukoencephalopathy (DPHL) is a rare condition is possible with opioid overdose and is often overlooked (Gallegos and Soleimani, 2016)

Some features from Journal of Health and Medical Informatics

Acute opioid withdrawal
 Group therapy
 leucoencephalopathy
 Cause acute mental
 Medication supply model
 Novel medication
 Novel medication supply
 benzodiazepines
 bilateral subcortical white
 laws
 barbiturates causes
 shared medical appointments
 Metabolism
 Brain
 Sex specific

Appendix E

Some discussions from JAMA are below

- There are factors influencing healthcare professional's prescribing behaviors as opioids prescribed following a surgery are associated with the rescheduling of hydrocodone. Therefore opioid policies should require follow-up to address unintended effects (Habbouche et al., 2018)
- In opioid prescribing change and postoperative prescribing, clinician-mediated and organizational-level interventions are powerful tools (Wetzel et al., 2018). ORADEs are associated with worse cost outcomes (Shafi et al., 2018) .
- There is a risk of subsequent hospitalization within 5 months of stopping the overdose and therefore it's better to transition to alternative treatments (Raol and Diallo, 2018).

Some features from JAMA

surgery
 hospitalization
 Hydrocodone
 change opioid prescriptions
 schedule change opioid
 schedule change
 Schedule
 administration
 ORADE
 higher risk subsequent
 history stopping
 history stopping prescription

Appendix F

Some discussions from Health affairs are below

- Policy makers may need to consider opioid crisis's effects on child while determining the public health policy (Quast et al., 2018). Robust PDMPs (Robust Prescription Drug Monitoring) is required to reduce opioid overdose as not all states are doing the PDMP well (Haffajee et al., 2018).
- focus on overdose and abuse dependence is increasing (Dick et al., 2015))
- There is evidence that it's not good for State Medicaid save money or ensure safety (Clark et al., 2011).

Some features from Health Affairs are below

Child welfare

geographical distribution physicians

prescription drug monitoring

drug monitoring programs

opioid abuse dependence

medicaid

accident support physicians

buprenorphine

Appendix G

Some discussions from European journal of public health are below

- Patients should be suggested to refrain from driving when starting an Opioid therapy as there is evidence that shows there is a higher risk of accidents (Cadenas-Dimate et al., 2015) Shift in pharmacy dispensing of opioids differed in males and females in Belgium and Norway (De Ridder et al., 2013).
- Low availability and high prices lead to low access of opioids in Albania therefore access and price are important factors (Grabocka and Docacaj, 2014)

Some features from European Journal of Public Health are below

risky sexual

Accidents

Albania

Sexual

Norway

Belgium

Saudi

Drivers

Hiv

overdose

Appendix H

A discussion from Annals review

- Opioid disorder treatment should integrate physical and mental health and embrace evidence-based care (McCarty et al., 2018)

Some features from Annals review

opioid use disorder

embrace evidence

integrate physical mental

prevention

Appendix I

Some discussions from AJPH are below

- Physicians received payment for opioid prescribing therefore there should be check on industry influences for opioid prescribing (Hadland et al., 2017)).
- Laws and enforcement of these laws in pain clinics may reduce opioid overdose deaths (Kennedy-Hendricks A, 2016).
- High prescription drug overdose has been reported in the rural areas (Paulozzi, 2006)
- There are been an illegal online sale of prescription opioids based on many tweets (Mackey et al., 2017)
- Physicians are not likely to prescribe opioid medication to Black population and white population is affected with opioid overdose the most.

Some features from AJPH are below
payments

pain clinics enforcement

availability Illegal markets

prescribed blacks whites

rural

indian health service

white

Appendix J

- Some discussions and features on opioid policy Twitter are below. Some sentiment words are policy, failure, failures, worst, warn, opinion. Country sentiment - America

Theme	Example
Opinions and facts	<p>Opioid settlement proceeds should be used to address substance abuse</p> <p>Arbitrary legislation will not fix a problem that has not responded to arbitrary measures</p> <p>The relationship between marijuana and opioid use is among of the best-documented aspects of marijuana</p> <p>A new study says policy makers and front-line care providers need to work together and come up with a multi-layer</p> <p>The disconnect between Trump's stated policy in 2017 and his actions</p> <p>When the crack epidemic hit, it was a "criminal" issue. Now that the opioid epidemic has hit white, rural America</p> <p>Prohibition & BAD POLICY is killing thousands every year in MA - NOT drugs on their own. As the supply of prescription opioids black market fills the void with, more other drugs. The Drug Prohibition Is to Blame for Opioid Crisis legislation is not the right way to do it. Another editorial on medication assisted therapy policy failure.</p> <p>Health policy researchers warn the Trump</p>
Country related	<p>BAD POLICY is killing thousands every year in MA - NOT drugs on their own</p> <p>When the crack epidemic hit, it was a "criminal" issue. Now that the opioid epidemic has hit white, rural America</p>

Top Features of opioid policy

Feature	value
policy	16.21726093
opioid	10.34624714
experts	6.263760299
legislation	5.784919702
Right	4.430411497

Appendix K

- Some discussions and features from opioid crisis Twitter are below. Some sentiment words are church, God, purpose, hope, love, pray, saddened, Jesus, good, innovative, strong leadership. Country sentiment - America

Opinions and facts from opioid crisis Twitter

Theme	Example
Opinions and facts	<p>New Opioid Policies leave some Cancer and Post-Surgical Patients without painkillers #Opioid Crisis</p> <p>When surgeon says no pain meds post op say then cancel the surgery I will wait until your ethics to return.</p> <p>We had eight cases in the last 60 days in which paramedics administered the drug Narcan, Killer drug results in alert</p> <p>Doctors write 214 million prescriptions for opioids yearly. That's two-thirds of the American population</p> <p>A large new study of #Medicare patient finds that over 90% on Rx #opioids have little to no risk of an #overdose.</p> <p>A rare opportunity to hear how we came to the #opioidcrisis. Its bigger than the AIDS crisis of the 1980s and a lot</p> <p>This is what I've been saying about postmortem toxicology being inherently unreliable and flawed as a measure and basis</p> <p>That was my exact question Gypsy. It is so upsetting that they are using cash to BRIBE physicians</p> <p>The Sacklers are the reclusive billionaire family blamed for America's addiction to #OxyContin. Now legal action</p> <p>Dr. Kline explains that there is a large difference between what the opioid crackdown claims to be and what it actually</p> <p>terrible problem. people committing suicide for being forced to stop opioids</p> <p>Neonatal Abstinence Syndrome Better Treated With #Buprenorphine</p> <p>I sincerely do #pray the generational curse of #addiction is broken without delay around the globe</p> <p>When surgeon says no pain meds post op say then cancel the surgery I will wait until your ethics to return.</p> <p>8 people in a family made the choices that caused epidemic</p> <p>We're developing safe-prescribing training for opioids at @amplifire_learn. As a relative of someone with #chronicpain, I was wary that the #OpioidCrisis was overblown and that patients who need painkillers to function were at risk</p> <p>structural barriers and ofcourse persistent gaps in treatment</p> <p>Damn, hospital visits due to edible marijuana use gets more national tv coverage than the raising opioid epidemic</p>

Appendix K (continued)

Very important to "understand the crucial distinction between opioid addiction and opioid physical dependence

A Society that does not treat people in pain is a society with serious problems. What's been happening to African Americans FOREVER is now happening to Whites. #opioidcrisis #ruralhealth

We need to extend this to school psychologists, social workers and counselors!

Kids in rural MO do not have access to school-employed mental health professionals and have to drive more than 30 miles from their homes for community-based mental health providers! #opioidcrisis

Overdose prevention through #BOOST offers those with opioid use disorder more support to stay connected to treatment.

43 overdoses in a single night in Vancouver: firefighters.

Addicts will find opiates. Sadly, less prescription writing & supply reduction by DEA/police, create more deaths.

Addicts will find opiates. Sadly, less prescription writing & supply reduction by DEA/police, create more deaths.

Stigma is a larger problem than overuse of medication to treat

Is this America's most hated family? #OxyContin & #OpioidCrisis & #Sackler family

Church With Him forever and ever and into the beyond...#Intercession #TwinSoul #OpioidCrisis #Alcoholism #CelebrateRecovery!

God now in our heart our journey has just begun

Make it true #God via your good Son that my #intercession for the past 17+ years has not been in vain

I sincerely do #pray the generational curse of #addiction is broken without delay around the globe!#Intercession #OpioidCrisis #TwinSoul

The #prayer of hope. The #prayer of a #miracle healing upon us all on this beautiful!

The good Lord has provided excellent protection to me for the past 17+ years and I truly believe I would not be her

#God now in our heart our journey has just begun!#Intercession #TwinSoul #CelebrateRecovery #Jesus #JesusSaves

Questions With #substanceabuse weighing in as the number one killer among Americans why is this still an issue?

What Advice Do You Have For Parents?

Imagine if we treated the #opioidcrisis like an actual public health crisis?

imagine if resources were allocated to combat?

Is opiate pain medicine no longer the drug of choice as it has been since 3400BC? my my who made that decision?

Is this America's most hated family? #OxyContin & #OpioidCrisis

The Sacklers are the reclusive billionaire family blamed for America's addiction to #OxyContin. Now legal action

What is outpatient treatment and how will it help those suffering from addiction?

Appendix K (continued)

Top features from opioid crisis Twitter

Feature	Value
opioidcrisis	27.63021735
pray	10.41878251
pain	9.887970313
addiction	7.578494618
hope	7.166411452

Appendix L

- Some discussions and features from neonatal abstinence syndrome and NAS are below.

Some sentiment words are rude, angry, sad, worse for neonatal abstinence syndrome

Some sentiment words are increase, best practices for NAS

Opinions and facts from opioid NAS

Theme	Example
Opinions and facts	More than a 5-fold increase in neonatal abstinence syndrome was estimated in the decade between 2004-2014 in the USA Recovery is possible families can be unified

Top features from Neonatal Abstinence Syndrome

Feature	Value
astinence	6.941529952
neonatal	6.941529952
neonatal astinence	6.941529952
syndrome	6.830846323
withdrawal	3.728124386

Top features from NAS

Feature	Value
nas	59.71452973
worse im sure	1.122140463
race	1.120057989
sad	1.101751758
changing	1.100277827

Appendix M

- Some discussions from Morphine Twitter are below. Some sentiment words are horror, danger, anger

Opinions and facts from morphine

Theme	Example
Opinions and facts	<p>Prescription Opioids were restricted due to Heroin OD which legislators determined prescription opioids led to Heroin use. Fentanyl synthetic is the triple toxic drug 100x more potent than morphineHow opioids affect the brain:</p> <p>Fentanyl = viral tweet</p> <p>Hydromorphone = 1,000 RTs(retweets)</p> <p>Opioids are demonized by the current times and for good reason...but I can assure you that morphine (or its equivalents) are still the “gold standard” for pain due to cancer. I hope your loved one can gain some relief soon!</p> <p>Scotland has the highest rate of drug deaths in the EU,</p> <p>they gave me a morphine drip for my pain. but i had a different surgery. I'm glad you are on the road to getting better. I'm rooting for you. :)</p> <p>Opioids are demonized by the current times and for good reason...but I can assure you that morphine (or its equivalents) are still the “gold standard” for pain due to cancer. I hope your loved one can gain some relief soon!</p> <p>Human saliva has a painkiller called opiorphin that is more powerful than morphine.</p> <p>Whole generation of docs don't know how to prescribe or use #morphine.They are afraid and can't be trained</p> <p>Me too. I was taking 80mg of morphine a day too, addicted to them both. Cannabis helps more than both combined.</p> <p>This thread is educational. Take away: do not give morphine for a headache</p> <p>I had some morphine and it was scary how good it felt and how often I began to feel like I needed more without realizing it</p> <p>wish i had some methadone or morphine rn i am feelin vry suicidal haha goodnight I guess see y'all tomorrow when nothing will have changed and I'll still be depressed</p> <p>Do not faint ladies and gentlemen the doctors have sent me home with Morphine happy days for me..</p> <p>accuse the eight family members of playing dangers of the painkiller</p>
Questions	<p>I have questions and can't ask Seligman! Does that mean taking morphine suppresses the immune system function too 🤔Why do you think evolution lowers immunity of depressed people. Maybe evolution thinks better those depressed get sick and die leaving their problems behind ?</p>

Opioids are
not the main
topic

Appendix M (Continued)

like nicotine, heroine, morphine, i'm a fiend and you're all i need, all i need, y
I'm on the verge of painting with my brains
Help me
Whiskey and morphine, rushing through me

Top features from morphine

Feature	Number
Morphine	42.67126159
Lmorphine	16.80409325
Thirstythirsty	9.547406832
happeningoxycod	8.786034406
morphinelaze	7.511872942
cheat lie names	0.231766895
lie names morphine	0.231766895

Appendix N

- Some discussions and features from Hydrocodone are below. Some sentiment words are crazy, happiness, findings, accuse family, god

Some opinions and facts from hydrocodone

Theme	Example
Opinions and facts	<p>Don't buy into this. Since I was seriously injured in 1997 I have been taking hydrocodone on a daily basis at the max prescribable amount. The problem is doctors not explaining the instructions. Taken properly this is not a dangerous drug. It's time released but wears off some of these jaw dropping testimonies of addicts of how they got "hooked" by the pharmaceutical companies. Like cough medicine containing hydrocodone. Few if any manufacture such a thing. Codine, yes but something that strong would be a special order item. Not randomly given Today I was prescribed an insane amount of hydrocodone for an extremely minor procedure performed at my PCP that : How opioids affect the brain:</p> <p>Fentanyl = viral tweet Hydromorphone = 1,000 RTs, featured in "what's happening" Oxycodone completely crazy, like it was all in my head. Yet the only thing I knew was real was the extreme insecurity those days, waking up in pain, I didnt want to wake up at all. Which led to naproxen, then vicodin, hydrocodone, percocet, slowly moving to oxy. Being told by doctors</p>

Some features from hydrocodone

Feature	Value
hydrocodone	22.63062497
especially important doctor	4.021632527
featured whats happeningoxycod	4.006629411
real extreme insecurity	2.249244359
addicts got hooked	2.239007643
dropping testimonies addicts	2.239007643

Appendix O

- Some discussions and features from fentanyl are below. Some sentiment words are hope, sadness, dangerous, tragedy

Some opinions and facts from fentanyl

Theme	Example
Opinions and facts	<p>linked suicides to forced tapers. Abandonment must be even worse. Patients with long term doctors suddenly drop</p> <p>Using prohibition to fight fentanyl is like using gasoline to fight fire.</p> <p>Prohibition is the cause of fentanyl.</p> <p>diagnosed the problem incorrectly.</p> <p>Legal prescribed pain medicine is NOT the problem. Illegal/illicit white powder fentanyl</p> <p>Dependence is NOT addiction. Dependence is NOT addiction.</p> <p>I think a reason they give fentanyl before surgeries is not just the pain management</p> <p>1 kilogram of fentanyl which is only 2.2 pounds can kill 500,000 people! This is a serious chemical weapon made</p> <p>Go after big pharma and you are going to save 0 lives.</p> <p>Illicit fentanyl is what's killing people.</p> <p>Did you see this? Almost every news story blames addiction on transitioning from a needed prescription to a street drug.</p> <p>No one can differentiate suicide and the Epidemic of Death directly caused by #fentanyl</p> <p>Fentanyl deaths spiking</p> <p>The U.S. Opioid Epidemic's Third Wave Begins</p> <p>She doesn't have a clue that the even the FDA data show that prescription pills are NOT the problem</p> <p>Economic supply chain issues contribute to the explosion of fentanyl use and deaths since 2013:</p> <p>Death rates from fentanyl among African Americans Hispanics are rising fast.</p> <p>#Fentanyl deaths skyrocketed</p> <p>Our poor baby surgery on Tuesday for him he has a fentanyl patch on his tail his heart was racing from the pain</p> <p>Excellent point. The worst villains identified, why go after other opiates with such unnecessary zeal? It isn't prescribed opiates as much as fentanyl & heroin as the largest killers, yet all are lumped together to maintain an agenda of misinformation. Who wins?</p> <p>Over 50 people in the U.S. died daily from fentanyl overdoses in 2016</p>

Appendix O (Continued)

An Ohio police officer recently claimed to have overdosed after brushing fentanyl residue off his uniform.
 Let's not mislead with generalized numbers because that distorts the facts.
 When responding to an overdose, every second matters. Reversing an overdose just a few seconds or minutes earlier
 Did you see this Almost every news story lames addiction on transitioning from a needed prescription to a street drug!

You think pharma is behind street fentanyl over doses
 Trafficker Christopher Bantli Convicted of Drug Importation Conspiracy

Country related Fentanyl comes from China. Check out the Opium Wars that China lost and the century of humiliation

We need to address the stigma associated with drug use. We need to do better.

It happened to my family. Last summer my 47 yr old baby brother died from a fentanyl O.D./brain bleed. One of these things led to the other.

yuma needs to put this fentanyl epidemic to a stop.

rest in peace to francisco lopez. to anyone that knew him im sorry for your loss.

If such little amount of this drug can kill someone then why the hell are pharmaceutical companies producing it?

The dosage of fentanyl that can kill you is equal to a grain of sand... a GRAIN OF SAND, and yâ€™all still fucking with sâ€™

One of the great evils of our time has been how opioids poisoned America, murdering thousands and reshaping communities

Please people stop preventing people from getting the pain meds they've been on for years.

Appendix O (Continued)

Top features from fentanyl

Feature	Number
kamala harris	9.004055283
police	6.7473359
illegal	5.198367735
trump	4.016297319
president	3.701514066
white house	3.070126657
policies	2.911892331
family	2.887357295
manufactured	2.805391555
crisis	
cdc	2.7557116
chronicpain	2.665040941
opioidhysteria	
chronicillness	

Appendix P

- Some discussions and features from codeine are below. Some sentiment words are denying patients, good news

Some opinions and facts from codeine

Theme	Example
Opinions and facts	<p>Kano is the highest centre for the consumption of codeine and hard drugs.</p> <p>When prescribed there was very little discussion of the side effects (especially when prescribed along with codeine).</p> <p>Thatâ€™s what I was going to say. The codeine is magical stuff</p> <p>Naltrexone is what is used to deal with alcohol addiction but as a full antagonist cannot be used</p> <p>Too many doctors that have never dealt with chronic pain themselves are denying patients opiates</p> <p>: How opioids affect the brain:</p> <p>Fentanyl = viral tweet</p> <p>Hydromorphone = 1,000 RTs, featured in "what's happening"</p> <p>Oxycodone</p> <p>Yeah, I've been on rotation between codeine, tramadol or morphine for 19yrs now depending on my pain level. I've obviously got to the point where I've built tolerance. My docs been trying something new tho, she's giving me lidocaine infusions. Only had 1 so far but it's helped 😊</p>

Some features from codeine

Feature	Value
denying patients opiates	2.469958549
doctors dealt chronic	2.469958549
discussion effects	
especially	2.399380511
alcohol addiction	1.966805082
brisane naltrexone	1.966805082

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VITA

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Academic qualifications

- **PhD Health policy administration, School of Public health**, University of Illinois at Chicago, 2019
- **Data Science Associate Certificate**, North Carolina State University, 2016
- **Master of Science in MIS**, University of Illinois at Chicago – 2004
- **Master of Science** in Computer Science Andhra University India- 2002

Research experience

- Obtained the significant predictors for Health Information Exchanges (HIE) using logistic regression
- Forecasted the adoption of technology and electronic medical records
- Analyzed healthcare sensitive data on decision support for data segmentation. Worked on EMR (Electronic Medical Records) and CCD (Continuity Care Document) on deterministic and probabilistic (machine learning) techniques for predicting the health and disease of a person and classifying the documents

Teaching experience

- University of Illinois at Chicago, Health policy administration
HPA 563: Web based Public Health Informatics
HPA 483: Management and Communication Systems for Public Health Informatics Applications
HPA 485: Legal and Ethical Issues in Public Health Informatics Applications

Work experience

- **Data Security Analytics Lead- Information Security Engineer**, Cisco Systems, 2015 to 2017 – Lead and managed teams and collaborated closely with stakeholders and customers, to align data science business objectives and deliverables to obtain desired ROI (return of investment). Savings of \$700K in costs and 3 weeks in time, along with 20%+ increased accuracy
- **Senior** – Zurich Financial Services, 2009 to 2010 - Strategized and executed data archiving, COBIT projects in US, Europe and Asia
- **Senior** - Ernst and Young LLP at Google, Cisco, 2005 to 2008 - Managed large, complex projects and provided advisory services to clients on assurance, data analytics, change and release management, implementation integrity, Sarbanes-Oxley compliance, business process redesign and control/process optimization.

Interests /Volunteer Experience

- Coordinator, Silicon Andhra ManaBadi - Set up the chapter in Chicago downtown area
- Coordinator, GGT Indian Temple Classes – Coordinator for after school activities for kids - Music, dance, and language classes in greater Chicago area

- Fund raiser – IDSO (Information and decision sciences) at UIC, 2003
- Volunteer, Stanford Asha for Education. Raised funds to provide education to underprivileged children in India
- Languages – English, Hindi, Telugu, German (basic)