

2019

Impact of Emergency Department Prescriber Type on the Rate of U.S. Opioid Prescriptions

Edward Worlanyo Agbevey
Walden University

Follow this and additional works at: <https://scholarworks.waldenu.edu/dissertations>

 Part of the [Health and Medical Administration Commons](#)

This Dissertation is brought to you for free and open access by the Walden Dissertations and Doctoral Studies Collection at ScholarWorks. It has been accepted for inclusion in Walden Dissertations and Doctoral Studies by an authorized administrator of ScholarWorks. For more information, please contact ScholarWorks@waldenu.edu.

Walden University

College of Health Sciences

This is to certify that the doctoral dissertation by

Edward Worlanyo Agbevey

has been found to be complete and satisfactory in all respects,
and that any and all revisions required by
the review committee have been made.

Review Committee

Dr. Lee Bewley, Committee Chairperson, Health Services Faculty
Dr. Donna Clews, Committee Member, Health Services Faculty
Dr. Mehdi Agha, University Reviewer, Health Services Faculty

Chief Academic Officer
Eric Riedel, Ph.D.

Walden University
2019

Abstract

Impact of Emergency Department Prescriber Type on the Rate of U.S. Opioid
Prescriptions

by

Edward Worlanyo Agbevey

MPH, Eastern Virginia Medical School, 2012

BS, University of Education, Kumasi Ghana, 2005

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Philosophy

Health Services

Walden University

August 2019

Abstract

Many drug overdoses in the United States are from prescription drugs, most of which are classified as opioid pain relievers (OPRs) and commonly prescribed in emergency departments (EDs) to treat pain. OPR abuse and addiction is a major public health issue. Researchers have identified the role of various patient characteristics (race, gender, demographics, etc.) in the variation in OPR prescription rates, but the contribution of provider-type differences to that variation has not been exposed. The purpose of this study was to evaluate the strength of the association between provider type and the likelihood of an opioid prescription by ED providers using national-level population data. Drawing from symbolic interaction theory, which served as the study's theoretical framework, it was postulated that the training and background of ED providers influence their interaction and OPR prescription decisions. The National Hospital Ambulatory Medical Care Survey 2015 data were used to evaluate the association between provider type and the likelihood of an OPR prescription, and the possible confounding effect of patients' race and payment type. Logistic regression analysis showed that attending physicians, consulting physicians, and physician assistants were more likely ($OR = 1.491$, 1.318 , and 1.315 , respectively) to prescribe an OPR in the ED, while controlling for age and pain level. Both race and payment type had predictive relationships with the outcome variable, but only payment type interacted significantly with provider type. These findings can serve as the basis for evidence-based training, procedure guidelines, and policy development, as well as inform patient-provider interactions, potentially leading to safer, more effective pain management encounters in the ED.

Impact of Emergency Department Prescriber Type on the Rate of U.S. Opioid

Prescriptions

by

Edward Worlanyo Agbevey

MPH, Eastern Virginia Medical School, 2012

BS, University of Education, Kumasi Ghana, 2005

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Philosophy

Health Services

Walden University

August 2019

Dedication

This dissertation is dedicated to my late mother, Mrs. Ann Akosua Nee Dzegblor-Tamakloe, for what she stood for in life. Love and affection with God's blessings are what you have left your children, and I have passed these attributes on to your grandchildren in your absence. Amen!

Acknowledgements

I am grateful to my beloved family for the time taken to complete this research work. My spouse; Mrs. Lucky Agbevey, and my children, Serena and Jerron, have gone through this enduring time with me, and I want to acknowledge them for the support they have shown me over the years in what was a challenging time. Thank you, and I ask God's blessings for your lives. Thank you, Dr. Lee Bewley and Dr. Donna Clews, for taking the time to review and accept my research work. You have inspired me with your feedback and encouragement to pursue a rewarding research product. I am most grateful!

Table of Contents

Chapter 1: Introduction to the Study.....	1
Introduction.....	1
Background.....	2
Problem Statement.....	7
Purpose of the Study.....	7
Research Questions and Hypotheses	8
Theoretical Framework.....	9
Nature of the Study.....	11
Assumptions.....	11
Limitations	13
Significance.....	13
Positive Social Impact.....	16
Summary.....	17
Chapter 2: Literature Review.....	18
Introduction.....	18
Literature Search Strategy.....	19
Theoretical Framework.....	20
Theoretical Concept of Symbolic Interaction Theory	20
Symbolic Interaction Theory in Nursing	21
Symbolic Interaction Theory in Mental Illness	23

Symbolic Theory in Current Research.....	24
Literature Review Related to Key Variables	27
The History of Pain.....	27
The Modern Era of Pain Management.....	31
Drug Addiction and the Opioid Epidemic	43
Prescription Opioids and the Variation in Prescription Rate	57
Summary and Conclusions	75
Chapter 3: Research Method.....	77
Introduction.....	77
Research Participants	78
The NHAMCS of the NHCS	78
Sample Selection for the NHAMCS	80
Sampling Process for the NHAMCS	81
Method of Data Collection.....	83
Field Representatives and Confidentiality	83
Instruments: Survey Material.....	84
Validity and Variance Estimation.....	85
Research Design and Approach	86
Secondary Data: NHAMCS Data Set	86
Sample Size Determination.....	87
Outcome or Dependent Variable: Rate of Opioids	90
Independent Variable: ED Provider Type.....	90

Covariate 1: Race/Ethnicity	92
Covariate 2: Source of Payment	93
NHAMCS Summary Data File Supplied by the NHCS	94
Statistical Research Design.....	95
Research Approach: Logistic Regression	95
Data Analysis	96
Research Question 1: Provider Type Variation	96
Research Question 2: Provider Type and Race.....	97
Research Question 3: Provider Type and Payment Type	98
Summary	99
Chapter 4: Results	101
Introduction.....	102
Descriptive Statistics.....	102
Demographic Characteristics	102
Predictor Variables.....	102
Dependent Variable: Opioid Prescription Outcome	111
Bivariate Analysis.....	112
Results.....	117
Research Question 1: Provider Type Variation	117
Research Question 2: Provider Type and Race.....	120
Research Question 3: Provider Type and Payment Type	123
Summary.....	125

Chapter 5: Discussion, Conclusions, and Recommendations	128
Introduction.....	128
Interpretation of the Findings.....	130
Descriptive Statistics.....	130
Research Question 1: Provider Type Variation	132
Research Question 2: Provider Type and Race.....	135
Research Question 3: Provider Type and Payment Type	137
Findings Related to the Conceptual Framework.....	137
Limitations of the Study.....	141
Recommendations.....	143
Implications.....	145
Conclusion	147
References.....	148
Appendix A: Patient Record Form	172
Appendix B: Hospital Induction Form	173

List of Tables

Table 1. Patient Demographic.....	104
Table 2. Prevalence of Provider Type.....	106
Table 3. Prevalence of Payment Type	108
Table 4. Descriptive Statistics of Confounder Variables.....	110
Table 5. Opioid Prescription Distribution.....	112
Table 6. Correlations of Continuous Variables.....	113
Table 7. Chi-Square Analysis of Association	114
Table 8. Chi-Square Analysis of Association	115
Table 9. Odds Ratio of Possible Confounders for Likelihood of an Opioid Prescription	117
Table 10. Odds Ratio of Provider-Types for the Likelihood of an Opioid Prescription	118
Table 11. Odds Ratio of Provider Types for Opioid Prescription Controlling for Age and Pain	119
Table 12. Odds Ratio of RACE for Opioid Prescription Probability	121
Table 13. Odds Ration of Race for Opioid Prescription Controlling for PAIN and AGE	121
Table 14. Odds Ratio of RACE, Provider Types, AGE, and PAINSCALE for Opioid Prescription	122
Table 15. Odds Ratio of PAYTYPER (Categorical) for Opioid Prescription	124

Table 16. Odds Ratio for RACE, AGE, PAINSCALE, and PAYTER for Opioid Prescription	124
Table 17. Comprehensive Model of Odds Ratio (RACE, AGE, PAINSCALE, All Provider Types, and Possible Interaction Variable) for Opioid Prescription	125
Table 18. Adjusted and Unadjusted p-values for Nurse Practitioner and Consulting Physician	134

List of Figures

Figure 1. Death from opioid overdoses.....	1
Figure 2. Variation in opioid prescription rate in an urban academic hospital ED	5
Figure 3. Death from prescription opioid overdose	14
Figure 4. Drug overdose deaths	50
Figure 5. Age-adjusted opioid analgesic poisoning rates, by race and ethnicity	60
Figure 6. G*Power analysis output.....	87
Figure 7. Histogram of age distribution	101
Figure 8. Histogram of PAINSCALE distribution	106
Figure 9. Histogram of IMMEDR (Immediacy) distribution	107

Chapter 1: Introduction to the Study

Introduction

Drug addiction is an epidemic that has gravely affected the United States health care system over the last few decades. The number of drug-related mortalities has been steadily increasing (see Figure 1), fueled, in part, by the rapid increase in deaths linked to opioid abuse (National Academies of Sciences, Engineering, and Medicine, 2017). According to Barnett, Olenski, and Jena (2017), there has been an increase in the prevalence of opioid prescriptions, despite no significant changes in pain presentation (see Figure 1). Today, opioid addiction is a problem for all regardless of social status as it affects everyone including addicts, their immediate family, and their community at large (National Academies of Sciences, Engineering, and Medicine, 2017).

As a public health problem, the opioid epidemic is uniquely tied to another major health issue, that of pain management. There are millions of Americans who are caught between the dilemma of needing to reduce their chronic pain and their use of powerfully effective but potentially addicting analgesics (Committee on Advancing Pain Research, Care, and Education, 2011). Responding to the opioid epidemic has been challenged by the fact that opioid abuse sometimes originates with an authorized prescription for the drug (Lembke, 2016; Sinnenberg et al., 2017).

Overdose Deaths Involving Opioids, by Type of Opioid, United States, 2000-2016

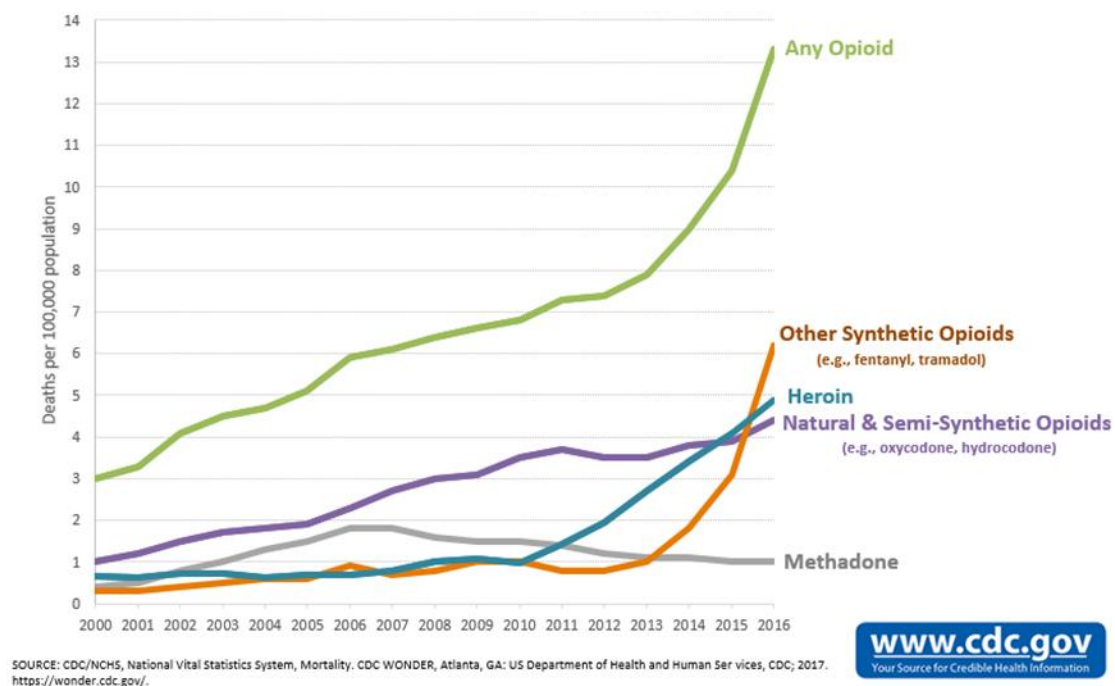


Figure 1. Death from opioid overdoses. Reprinted from “Overdose Deaths Involving Opioids, Cocaine, and Psychostimulants — United States, 2015–2016,” by P. Seth, L. Scholl, R. A. Rudd, and S. Bacon, 2018, *MMWR. Morbidity and Mortality Weekly Report*, 67(12), p.349-358. Copyright 2018 by Centers for Disease Control and Prevention.

Background

Pain is the most common complaint with which adult patients in the United States present to the emergency room. Out of the 131 million emergency department (ED) encounters across the United States in 2011, pain-related ailments were the most frequent reason for ED visits (Weiss, Wier, Stocks, & Blanchard, 2014). And in 2015, among those aged 18-64, approximately 34% of all ED visitors had an opioid ordered or

prescribed to them (Yacisin, O'Connor, & Akinseye, 2018). Moreover, there has been a significant increase in the rate of opioid prescription in EDs over a decade now, an increase not accounted for by any increase in the presentation of pain-related complaints (Mazer-Amirshahi, Mullins, Rasooly, Van Den Anker, & Pines, 2014; Murthy, 2016; Patel & Afshar, 2017). The cause and the effects of this increase in opioid prescription and its possible connection to the present-day opioid epidemic has garnered the attention of researchers.

There are several options for treating patients who present with pain, the most common of which is to prescribe an analgesic. Opioids, though very effective as a pain reliever, are also highly addictive, and many people who are initially prescribed these medications for medical purposes end up misusing them (Broida, Gronowski, Kalnow, Little, & Lloyd, 2017; Jeffery et al., 2018; Substance Abuse and Mental Health Services Administration, 2016). Unfortunately, there are opioid-naive (never used opioids before) patients who become addicted after having been introduced to opioid drugs at the ED (Hoppe, Kim, & Heard, 2014). Additionally, patients dealing with health issues and who more frequently visit the ED tend to have a higher prevalence of opioid abuse (Han et al., 2017). This finding implicates ED opioid prescription in the opioid epidemic dilemma.

Pain management, the practice of treating patients presenting with all types of pain, is essential to quality health care, but it may be hindered by implicit biases and disparities in analgesic therapy. Studies focused on opioid prescription rates in emergency settings have shown some of the many factors related to the biases between the patient and their prescriber (Barnett et al., 2017; Knopf, 2017). Some of the factors

that account for the variation in prescription rate include patient characteristics such as age, gender, race/ethnicity, and source of payment (Hollingshead, 2016; Knopf, 2017). Other researchers have uncovered that patients' race and socioeconomic status are the major contributors to opioid prescription rate variation (Singhal, Tien, & Hsia, 2016; Sinnenberg et al., 2017). These prescription rate variations have had serious implications for the disparity in pain management among minority population groups in the United States (Singhal et al., 2016).

Yet, other studies on the role of the ED in the rampant abuse of opioid drugs in the United States have implicated not only the characteristics of ED patients, but those of ED health care professionals who do the prescribing (Bartley et al., 2015; Pomerleau, Schragger, & Morgan, 2016). Researchers have found that prescriber- or provider-type qualities including age, gender, race, level of experience, and specialty influence the rate at which opioids are prescribed (Porucznik, Johnson, Rolfs, Sauer, & Porucznik, 2014; Sinnenberg et al., 2017). In a study of Medicare recipients, Barnett et al. (2017) found that the rate of opioid prescription in the ED varied significantly, from 7.3% to 24.1%, among different hospitals. Another study demonstrated the significant amount of variation that can exist among providers at the same institution, for patients who present with the same condition (see Figure 2; Hoppe, Mcstay, Sun, Capp, & Hess, 2017). Studies like these point to the complicated nature of opioid prescribing and the complex involvement of prescriber bias. Understanding the prescriber to patient interaction and the factors involved in prescriber decision-making is important to the development of

policies and procedures that are aimed at curbing the opioid pain reliever (OPR) abuse epidemic.

The burgeoning opioid crisis made evident the need for policy re-evaluation, and consequently in 2013 many different States implemented new procedures (Beaudoin, Janicki, Zhai, & Choo, 2018). These new value-based practice guidelines for physicians were intended to influence the way they practice medicine and streamline their prescription decisions and behavior. However, recent research revealed that these policy changes were ineffective and 4 years later the expected savings were unrealized (Bonfrer, Figueroa, Zheng, Orav, & Jha, 2018). Regarding opioid prescription in the ED, although the overall rate decreased slightly, the variation in frequency of opioid ED prescription among provider type persisted (Beaudoin et al., 2018). According to Vivolo-Kantor et al. (2018), despite data implying a stabilizing of prescription rates, the opioid overdose problem is worsening, with rates continuing to rise from 2016 into 2018. The exact reasons for and the underlying drivers for the differences in OPR prescription rates among the various provider types remain unclear.

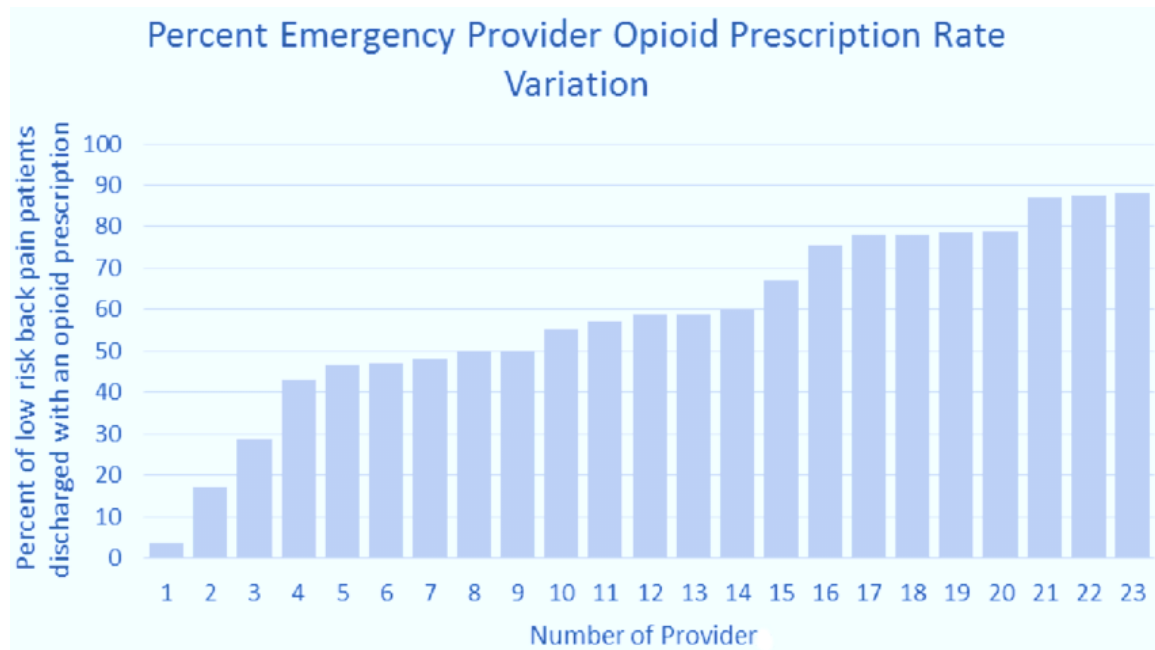


Figure 2. Variation in opioid prescription rate in an urban academic hospital ED. (Hoppe et al., 2017).

Understanding the role of the provider in the ED is an important component of opioid prescription variation. As Michael et al. (2018) concluded, more research is needed to counter cognitive dissonance and the absence of self-awareness among providers and to foster greater ED prescribing policy compliance. Understanding the vulnerabilities and unconscious biases involved in ED OPR prescription variation can help medical groups design improved prescription guidelines and standardize emergency responses to pain (Lembke, 2016). Hopefully, the findings from this research will inform providers, policy makers, and the stakeholders involved in reducing the risk of OPR addiction and help promote more effective solutions to the opioid epidemic.

Problem Statement

There are many factors, mostly related to the nature of the interaction between the patient and the prescriber, involved in the prescription of opioids. Unraveling the variables associated with an initial opioid prescription, recurrent use, and eventual abuse is critical to a sustainable solution to the OPR epidemic (Beaudoin et al., 2018; Csiernik, 2016). Many studies underscore the role of patients' characteristics, namely their race, ethnicity, age, gender and demographics, on the rate of ED opioid prescription (see Barnett et al., 2017; Han et al., 2014; Knopf, 2017; Manchikanti et al., 2012; Pletcher, Kertesz, Kohn, & Gonzales, 2008; Tamayo-Sarver et al., 2003). Fewer researchers have examined the role of the provider on the rate of ED opioid prescription, however; these studies have yielded evidence of significant variation but have been limited by size and scope (see Hoppe et al., 2014; Pomerleau et al., 2016; Smulowitz, Cary, Boyle, & Jagminas, 2016). It is now believed that understanding the nature and the impact of provider type on the rate of ED opioid prescription is essential to the development of provider-specific prescription guidelines that improve ED pain management strategies and minimize the contribution to the opioid crisis (Ganem, Mora, Varney, & Bebart, 2014; Michael et al., 2018).

Purpose of the Study

There are several studies concerning the issue of ED opioid prescription but few have included an examination of the relationship between provider type and the rate of opioid prescription, and those that have were either pilot studies or limited to a specific hospital or patient group. This quantitative analysis was the first, according to my review

of the literature, to evaluate the strength of the association between provider type and the likelihood of an opioid prescription by ED providers using population data collected on the national level. I sought to explore the complicated dynamics between opioid prescription and potential opioid abuse by highlighting the impact, if any, that different types of health care professionals have on the opioid prescribing rate and rate variability in EDs across the United States.

Research Questions and Hypotheses

The focus of the study's three research questions (RQs) was on providing insight into the proposed association between the provider type and the probability of emergency department opioid prescription. The RQs and corresponding hypotheses were, as follows:

RQ 1: Is there a statistically significant association between provider type and probability of opioid prescription in the ED?

H_01 : There is no significant association between provider type and probability of opioid prescription in the ED?

H_{a1} : There is a significant association between provider type and probability of opioid prescription in the ED?

RQ 2: Is the association between provider type and the probability of opioid prescription influenced by the race/ethnicity of the patient?

H_02 : The association between provider type and the probability of opioid prescription is not influenced by the race/ethnicity of the patient.

H_{a2} : The association between provider type and the probability of opioid prescription is influenced by the race/ethnicity of the patient.

RQ 3: Is the association between prescriber type and the probability of opioid prescription is influenced by the patient's "expected source of payment" variable?

H_{03} : The association between prescriber type and the probability of opioid prescription is not influenced by the patient's "expected source of payment" variable.

H_{a3} : The association between prescriber type and the probability of opioid prescription is influenced by the patient's "expected source of payment" variable.

Theoretical Framework

Researchers commonly use symbolic interaction theory (SIT), also referred to as the symbolic interactionism, to study how individuals behave in different settings. SIT is a social science theory and provides an explanation of the nature of the different types of relationships that exist within a society (Hari, Henriksson, Malinen, & Parkkonen, 2015). The theory is premised on the idea that a society is the result of everyday interaction among people and that, as a result of these social exchanges, individuals develop unconscious patterns of behavior (Aksan, Kısac, Aydın, & Demirbuken, 2009). Several decades ago, health care researchers, specifically nursing researchers, applied SIT to explain how patterns of hierarchy influenced the nurse-patient relationship and the outcome of nursing care (Chapman, 1976). More recent researchers have used SIT to develop models or causal pathways for certain health problems to guide the development of health intervention strategies (Noyes, 2017).

According to SIT, individuals live in a symbolic world, and the nature of any social interaction is subconsciously influenced by the particular interpretations of the symbols encountered as individuals interact with others (Aksan et al., 2009). This theory

is premised on three main assumptions that provide a basis for analyzing interactions to find solutions to problems of a social nature. These assumptions include the following: (a) an individual's behavior is based on the meaning he or she has constructed about his or her world, (b) an individual's action is in response to the meaning he or she has assigned to the actions of others, and (c) the meaning that an individual assigns to the behavior of others is based on his or her own personal experience (West & Turner, 2018). According to Redmond (2015), humans are social beings and they create their world based on social interaction, *but* they are also actively thinking (as opposed to passive conditioning) beings that are constantly defining and redefining their world based on their interactions with others.

Social science frameworks may be beneficial to health care research design and improve the understanding and interpretation of the findings. The positivistic approach, with its propensity for quantification analysis, is more common in public health and epidemiology research. However, social science frameworks are better suited to understanding issues of drug addiction and the social nature of its impact and to developing suitable intervention strategies (Maycock, 2015; Patulny, Siminski, & Mendolia, 2015). In this study, I assumed that the patterns of behavior of health care practitioners working in the ED are influenced by their training and background and that these factors affect their interactions with patients. I also assumed that practitioners' prescribing decisions are also affected by their perceptions of their patients based on their physical qualities (as reflected by their race or age) and their socioeconomic status (as reflected by the source of payment). It is these assumptions that I attempted to provide

insight on in conducting this investigation. The findings should elucidate the nature of the relationship between the ED provider type and patients and its effect on opioid prescription dynamics.

Nature of the Study

This study involved a quantitative statistical analysis of retrospective cross-sectional data. I used data from the ED section of the National Hospital Ambulatory Medical Care Survey (NHAMCS); the relevant variables were from those who visited the ED and were not admitted (CDC/National Center for Health Statistics [NCHS], 2017). The outcome or dependent variable (DV) was categorical and was the *Yes/No* (dichotomous) response to whether an opioid was prescribed during the visit. The independent variable (IV), provider type, was also categorical (attending physician, resident physician, physician assistant, nurse practitioner, and physician consultant). To answer the first research question, I used a univariate logistic analysis to evaluate the association between the IV and DV, while controlling for age and painscale measure. For the second and third research questions, multivariate logistic analyses were used to assess the effect of potential covariates (race/ethnicity of patient or the expected payment plan of the patient) on the main (provider type/prescription rate) regression formula.

Assumptions

I analyzed secondary data from the 2015 NHAMCS. The makers of the survey collected cross-sectional data on patient visits to the EDs from all 50 states in the United States, excluding those from federal, military, and Veterans Administration hospitals for the year 2015 (NCHS, 2015a). The data they collected were generated from the electronic

records associated with patient record forms or PRFs and were based on patient visit weight estimates, for which the relative standard error was less than or equal to 30% (NCHS, 2015a). The NHAMCS survey is one of many surveys administered by National Health Care Surveys to record health care utilization activity among the different types of health care providers across the United States.

The NHAMCS data is shared publicly for analysis and the assumptions is that the data were accurately collected and recorded and is representative of the entire population. The sampling was conducted with a four-stage sampling design: (a) primary sampling unit (counties), (b) hospitals within those primary sampling units, (c) clinics within the outpatient departments, and (d) patients visits within emergency service areas (NCHS, 2015a). Of the 457 EDs selected, 377 were eligible, resulting in a 70.8% (68.7 weighted) response rate (NCHS, 2015a). The electronic PRF data from 100 randomly selected patients from each of the participating institutions were collected over the systematically assigned 4-week reporting period (NCHS, 2015a). The data was then cleaned, compiled, and published on the CDC/NCHS website.

The NHAMCS incorporates various measures of quality control to ensure the accuracy of the data collected. Attempts were made to minimize bias by using a multistage estimation technique that included: 1) trimming the overall probabilities for institutions that may be overrepresented; 2) weighting the responses from similarly sized institutions to account for non-responses; and 3) accounting for the seasonal reporting by shifting the extra weights among EDs in same quarter of the year (National Center for Health Statistics, 2015a). Internal validity testing revealed that the missing data may lead

to added variances, but the possibility of a Type I error could be minimized by choosing an alpha of 0.01 instead of 0.05 for the test of significant differences (National Center for Health Statistics, 2015a). Unlike in previous years, for 2015, all data were collected by assigned ‘Census Abstractors’ specially selected and trained by the U.S. Census Bureau (National Center for Health Statistics, 2015a).

Limitations

The limitations of this study are few and are based on the objective of the research questions. Even though the NHAMCS collects data from EDs as well as outpatient departments, only the ED data have been made public. Since the analysis uses cross-sectional survey data, no causal inferences (only correlational) can be made from the results. Also, the approximately 70% response rate, based on eligibility, could introduce some response bias (National Center for Health Statistics, 2015a). Finally, this study is limited to a specific time period, the year 2015 and to very specific independent (provider-type, race, payment source) and outcome (rate of opioid prescription) variables. Given that the study is limited to U. S. hospitals, the findings are valid and generalizable to ED settings in the U. S. alone.

Significance

The problem of opioid epidemic is getting progressively worse and has, deservedly so, become a most pressing public health concern. In 2010, of the 33,329 deaths from overdose of prescription drugs, 16,600 were the opioid analgesics medication (Poon & Greenwood-Ericksen, 2014). Over the next decade and a half, an increase in prescription drugs use paralleled an increase in heroin use and consequently an increase

in related deaths. Among those who try heroin for the first time, four out of every five had already been abusing prescription pain relievers (Poon & Greenwood-Ericksen, 2014). OPR abuse usually begins with a prescription and end with addiction.

There has been a reported 568,699 drug overdoses between 1999 to 2015 in the US, and in 2015 alone, 63% of the drug overdose deaths were caused by opioids (Puja Seth, Scholl, Rudd, & Bacon, 2018). According a report based on data from the Center for Disease Control and Prevention, “deaths from synthetic opioids are up 72%” (Rudd, Seth, David, & Scholl, 2016). Similarly, the age-adjusted rates for overdose of OPR has doubled from 2015 to 2016, with the rate an increase of almost 300% among Hispanics and an increase of approximately 400% in the Washington, DC area (Puja Seth, Scholl, et al., 2018). There is no doubt that the abuse of OPR is at epidemic proportion in this country and if not addressed will get progressively worse.

Number of Deaths from Prescription Opioid Pain Relievers

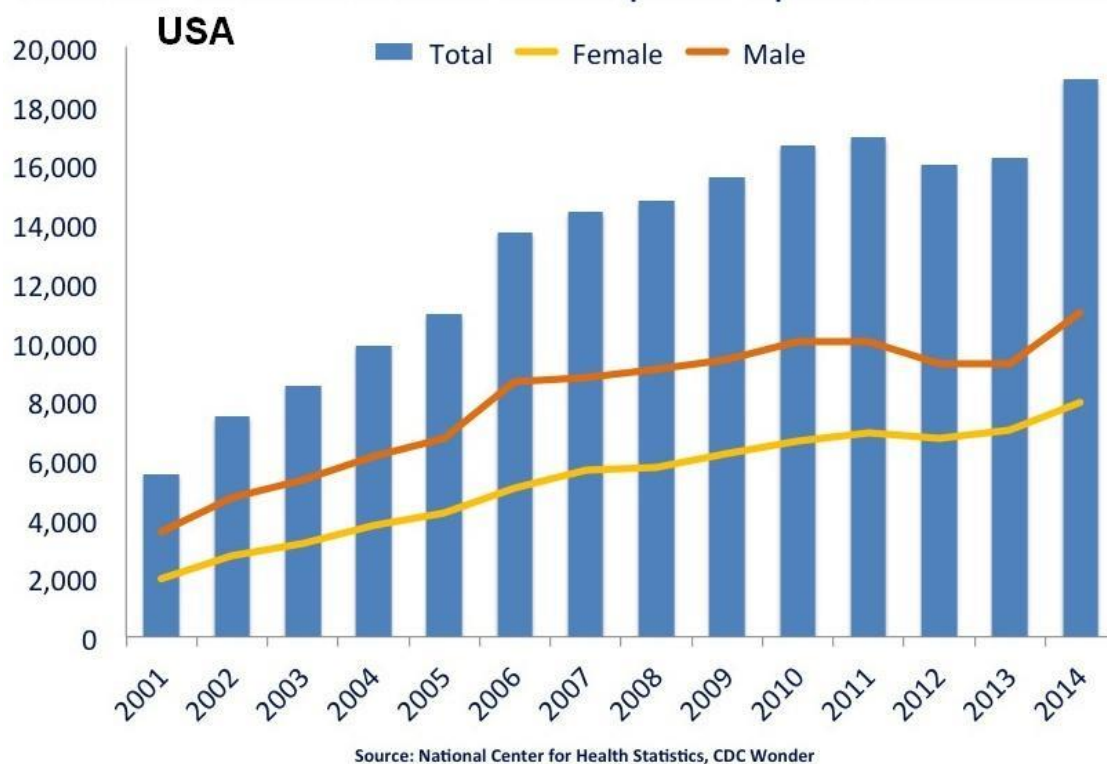


Figure 3. Death from Prescription Opioid Overdose. (Puja Seth, Rudd, et al., 2018).

The role of ED prescription in the opioid crisis is worth researching for a number of reasons. In the US, over two million individuals are dealing with an addiction to prescription opioids, and another 12 million are currently abusing opioid drugs in some form or another (Hughes et al., 2016). A study by Hoppe, et al. (2015) found that one in every six patient discharged from the ED was prescribed an opioid and that ratio was almost doubled when those admitted to the hospital were included. Research has indicated that abuse and addiction can be initiated from a legitimate opioid prescription (Butler et al., 2016; Lembke, 2016). Understanding the connection between ED prescription and opioid abuse and addiction may help create more effective policy.

The aforementioned numbers indicate the severity of the opioid epidemic and the possible role that ED prescribing may play. Therefore, tailoring solutions and strategies that effectively address the underlying drivers of this issue is critical to the success of any intervention program. It is the objective of this research to contribute information related to the opioid epidemic and opioid pain reliever prescription, specifically how the ED prescriptions rate varies and is influenced by the various ED provider-types. Educating the stake-holders and policy writers about this subject of prescription rate variation could be important to responding to and minimizing the negative impact of the opioid epidemic.

Positive Social Impact

The results of the opioid epidemic are widespread and far-reaching, and even today the rate of opioid abuse continues to rise (Vivolo-Kantor et al., 2018). It has now gotten much media attention, with the President Donald Trump and First Lady, Melania Trump getting involved to find a solution to this national crisis. The apparent solution is demanding of a multifaceted approach that combines the resources and expertise of all the stake-holders, of which the ED prescribers play an important role (Mazer-Amirshahi et al., 2014). The first step in reducing the impact of this dilemma is knowledge of the contributing factors and awareness of the nature of the role of each factor. The current need is for timely, insightful information gathered from the field, on which evidence-based intervention programs can be developed and implemented.

The positive social change implication of this study is two-fold. First, the information generated will add to the awareness of the providers about their biases and their partialities, both conscious and unconscious, and how those biases influence their

decision-making process and their prescribing behavior. Second, the information from the findings combined with other resources used to improve upon the existing policies and guidelines, fostering safer prescribing practices and better pain management services in the ED. This type of impact of beneficial to the patients, the providers, the institutions, and the policy makers as well as the society at large.

Summary

The problem of prescription drug abuse in the US is a major healthcare issue, and the increasing opioid addiction is partly responsible. Responding to the opioid crisis has been complicated by the fact that it is so closely linked to another healthcare dilemma-pain management. Pain is the most common reason for visiting the ED and every year several million patients leave with a prescription for an opioid pain reliever.

Unfortunately, many of these patients end up abusing these drugs, others become addicted, and some may even die as a result of the abuse. Several studies have found that the rate of opioid prescription in the ED is influenced by the patient's characteristics, including race, gender, age, and SES. Other small-scale studies have implicated certain qualities of the providers as well. The objective of this study is to investigate the role that provider-type differences has on the opioid prescription rate variation. This research was a large-scale study, utilizing data from the National Hospital Ambulatory Medical Care Survey (NHAMCS). The objective is that the findings will bring awareness to the issue and provide important insight guiding policy and procedure development related to the opioid epidemic.

Chapter 2: Literature Review

Introduction

The objective of this literature review is to illustrate the challenges related to pain management in the U.S. health care system and to detail the role of various risk factors driving the opioid epidemic. Much of the focus and research has been placed on patient-related factors and their role in the worsening opioid epidemic. But despite the recent implementation of prescription guidelines and other patient-related strategies for opioids, variation in prescription rates, especially among the various ED providers, continues. A few pilot studies have revealed that there are physician-related biases that affect their prescribing decisions and that these differences contribute to the variation but, without extensive, large-scale investigation, it is difficult to use the information. An increased understanding of the factors, some of which are unconscious, that influence the prescribing decisions of ED providers may help hospitals develop meaningful interventions that help to curb the rise in the rate of prescription opioid and positively impact the opioid abuse epidemic in the United States.

Chapter 2 begins with an overview of my literature search strategy, which is followed by a description of the theoretical foundation for my research. The literature review begins with a discussion of the history of pain through the ages and the various approaches used to deal with this longstanding health condition. The section that follows includes details on the history of pain management and the development of the field as it is known today. It also includes information about analgesics and how opium-derived drugs became some of the most common pain relievers. The next section includes a

description of the rapid rise in prescription opioid and opioid abuse, concurrent with the rise in opioid-related injuries. In addition, in this section, I discuss the conditions that facilitated addiction to opioids and the resulting epidemic, as well as the factors that predispose individuals to addiction. The final section of the literature review includes relevant research on the issue of opioid prescription and the variation in prescription rate and their role in the epidemic. The section closes with the particulars of the studies on ED prescription variation, with emphasis on the reasons why this is an important area that should be the subject of future research. The chapter ends with a summary of key points and a transition to Chapter 3.

Literature Search Strategy

For this literature research I used several online databases focusing on health and epidemiology. Most of the journal articles were found in the PubMed database, but several came from Google Scholar, Elsevier, Wiley, ProQuest, Medline, Ebscohost, Tandfonline, and CINAHL. I accessed these databases from Walden University Library. The search terms used included *opioid*, *opioids*, *opioid epidemic*, *pain*, *pain management*, *opioid prescription*, *opioid addiction*, *ED provider*, *opioid mortality*, *opioid abuse*, and *opioid prescription variation*. These were used either individually or in various combinations with the Boolean operators AND, OR, or NOT to restrict the results to those that were relevant and useful. I obtained some of the statistical information from websites belonging to the U.S. Department of Health and Human Services and institutions under it such as the Food and Drug Institution (FDA), National Institutes of

Health, and the CDC, especially its measles, mumps, and rubella section. I also utilized the journal sharing website ResearchGate to obtain articles not available in the databases.

There were many research articles to choose from, as the opioid epidemic has become a very popular topic of study. I narrowed my search to articles relevant to the topic of the role of opioid prescription rates in the opioid epidemic. Finding research articles that specifically addressed ED provider prescription variation was a bit more challenging. Reviewing the objective and the abstracts of each article provided valuable insight into the usefulness of the article to the study. Prioritizing the original research articles that reported important findings required a more extensive review of search results. Once I deemed articles relevant, I added them to an online Mendeley account and later to the offline version once it had been updated. In the offline account the articles were tagged and filed in various folders to facilitate easy retrieval of reference information for the reference list.

Theoretical Framework

Theoretical Concept of Symbolic Interaction Theory

I used the theory of symbolic interaction as the theoretical foundation for this research. The idea of SIT comes from social science and is credited to George Herbert Mead. Mead was a psychologist who laid the foundation for a unique approach into human social behavior by expanding on the concepts of *mind* and *me* (Benzies & Allen, 2001). It would only be labelled *symbolic interaction theory* by subsequent researchers who adopted his approach and included concepts of *I* and *me*. In essence, SIT states that individuals' concept of their world is based solely on their interpretations of what they

perceive in their world and it is this interpretation that governs their behavior (Benzies & Allen, 2001). SIT helps researchers to explain human behavior from a different perspective than simply what can be observed--from underlying thoughts and subconscious motivations.

Those who subscribe to SIT contend that the world individuals live in is made up of symbols and that all social interactions are based on individuals' interpretations of those symbols (Aksan et al., 2009). According to symbolic interactionists, there are three main assumptions that underly the theory and its use. They include the following: (a) that all human behavior is influenced by the individuals' perception of their world; (b) individuals' perception of their world is based on their interpretation of the symbols, both material and immaterial symbols; and (c) the interpretation that individuals assign to each symbol they encounter is based on their historical experience with that symbol (West & Turner, 2018). The SIT concepts define human interaction as dynamic in nature, one that is constantly being created and recreated by individuals' many social encounters and the actions they take in response to their interpretations of these encounters (Redmond, 2015).

Symbolic Interaction Theory in Nursing

Symbolic interaction theory (SIT) has been used for decades in the fields of psychology and social science as it useful for understanding and interpreting the different social dynamics that make up the society (Hari et al., 2015). According to Aksan et al. (2009), SIT not only explains the nature of the interactions and why they happen, it also provides insight into the unconscious patterns of behavior that exists in many social

settings. But SIT has been found to a flexible theory and has moved beyond the sciences to other fields including medicine and healthcare. It was first used several decades ago in nursing research to understand the dynamics involved in the nurse-patient relationship and how that relationship affects patient's health outcome (Chapman, 1976)) The researchers believed that combing sociology and nursing could provide insight into the behavior of both groups (nurse and patient) and how the patterns of power and compliance overlap to meet the respective objectives of each and how that insight could benefit both (Chapman, 1976). The research was a success and it provided the impetus for more research in the health field with SIT as the framework for analysis.

The social dynamics between the patient and the healthcare provider turns out to be quite suitable for the SIT based study. Another study ten years later, used SIT to study the nurse-patient interaction, but specifically in the emergency department setting. This study collected data from the in-depth interviews to understand the social symbols that influenced the nature interactions between and the behavior of the nurses towards their patients (Byrne & Heyman, 1997). The symbolic interaction theory was used to interpret the attitudes of their role and purpose as well as their discernment of their patient's behavior and to direct the analysis of the data. The definitions of their role were prioritized by a few factors and this governed their care approach. These factors included: treating the patients' injury; providing urgent care; the smooth running of the department; and fulfilling the role according department rules (Byrne & Heyman, 1997). The results indicated that the nurses were under pressure to ensure that the ED was running smoothly

during their shift, and this pressure resulted in them spending less time and poor communication with their patient (Byrne & Heyman, 1997).

Researchers used the theories like SIT to dig deeper into the meaning of the results, as was necessary if they were going to use the results to develop an intervention strategy. This led them to note that the nurses training and years of experience, in the ED and as a nurse in general, influenced how much pressure they felt and how much time they felt necessary to understand the concerns and anxieties of their patient (Byrne & Heyman, 1997). Some nurses needed less interview time and even used the ‘popping in’ technique as a means of calm their patient’s anxieties (Byrne & Heyman, 1997). Overall, the research was groundbreaking as it had led the way to what would become quite common- the use of social science theory in healthcare research.

Symbolic Interaction Theory in Mental Illness

SIT has also been used to provide the theoretical framework needed to interpret research findings as it relates to the problem of mental illness and the associated social stigma. A comprehensive literature review research on mental illness used SIT to identify the behavioral factors that may be hindering patient recovery or the administration of proper care (Roe, Joseph, & Middleton, 2010). The new policies that shifted focus on providing support by promoting improved sense of well-being as opposed to only curing, treating, or alleviating patient’s dysfunction. The proper implementation of these intervention would be largely dependent on the interaction between the patient and their healthcare professional, which is in turn influenced by the providers’ attitude towards their patient and their condition. The stigma of being a psychiatric patient, their

perception of the service they are provided could either enhance or exacerbate the mental and emotional issues. SIT was used to identify the context, the discourse and the expectations and interpretations of the variables in the cultural and social and critical examination that includes the exposures of hidden motives and unconscious biases (Roe et al., 2010). The findings, as interpreted by the SIT, revealed the importance of policies that address the social issues that contribute to the mental illness (Roe et al., 2010). The support provided by a positive social interaction, the most important of which is with their healthcare providers, can enhance the recovery process. SIT was also used to design intervention strategies that would foster a more constructive social interaction between the mental health patient and their caregiver.

Symbolic Theory in Current Research

SIT provides the framework for the research process that involves a social setting and fosters an understanding of the worldview possessed by each of the parties involved, their definition of the relevant symbols and the interpretation of these symbols that motivate the actions and behavior (Hari et al., 2015). Interpretations of the social symbols are governed by external as well as internal ideas, derived from past social experiences, with a presumption of a predefined 'me' and then what does this action mean to the 'me' I believe myself to be, are at the foundation of social interaction rituals (Patulny et al., 2015). The dynamic relationship between the self and the society is created by and then altered by further interactions based on the premises of the behavior of others, their interpretation of symbols their behavior conveys, and the reaction and dynamics generated from their response (Roe et al., 2010). The best method for interpreting human

behavior is through an internal and an external frame of reference, helps individuals make sense of both.

The use of SIT and other social science theories in quantitative healthcare research is having a positive impact. Like with the nursing research, SIT revealed that a definition of one's work priorities and perceptions of their patients both had a major influence on the nature and quality of the communication, and it affected the care that the patient received. Positivism and other theories of descriptive, correlational, causal-Quasi-Experimental, and Experimental were more common, but the social sciences are proving appropriate for select issues of healthcare that have a distinct social aspect (Maycock, 2015; Patulny et al., 2015). Theories like SIT can not only be used to design the research, it can elucidate the findings and then guide the development of an effective intervention strategy. Researchers are finding that defining nature of the interactions and subsequently creating programs for healthcare intervention is easier if theories like SIT are used to model the problem (Noyes, 2017).

For this current research program, SIT was chosen because of its propensity to enlighten social interactions, the symbols involved, and the patterns of behavior created. Here the ED providers as healthcare practitioners are interaction with their patients in the ED setting and this interaction is influencing the rate of opioid prescription and eventually having an impact on potential opioid abuse and misuse. Since most of the prescribing decisions are made subconsciously, a theory like SIT helps to uncover some of these biases that are below the surface and make them more aware of their behavior. Understanding the nature of the social interaction and the factors that are involved could

provide valuable information for crafting new policies governing prescription drugs or improving current ones.

This current study proposes that there are some very salient factors that influence prescribing decisions and these create prescribing patterns among the different types of providers. Characteristics such as a patient's race/ethnicity and their SES as perceived by the provider create stereotypes that then influence who gets prescribed an opioid analgesic. These providers, based on their level of training, their area of specialty, their respective roles in the ED, can factor subconsciously and create these persistent patterns of variation in prescription rates. Using theories like SIT to guide research can bring these subconscious factors to the awareness of the ED providers as well as the policy creators.

Literature Review Related to Key Variables and/or Concepts

The History of Pain

Pain in ancient times. Pain is a universal human experience and the oldest medical problem, it is also the most common reason for seeking medical care (Tompkins, Hobelmann, & Compton, 2017). Pain is an inevitable part of being alive, as all living creatures who poses a central nervous system share in the experience of pain. But pain is more than a biological reaction to a painful stimulus, it is also a complex mix of cultural, social, and psychological factors that play a role in its manifestation (Germossa, 2018). Pain has come to serve as an important signal of disease or injury in the body and its presence has a major impact on the quality of life (Colliers, 2018). But pain and the treatment of pain has had a long and fascinating history that is worth exploring.

The history of pain and pain treatment is filled with many colorful tales and in the earliest records. Those involved in treating the sick and practicing the art of healing have always been challenged with balancing the patients need for pain relief with that of any unwanted side effects of the administered pain therapy. In ancient times pain was regarded as the work of demons or evil spirits inhabiting the body of the sufferer. In those days, pain management was relegated to the work of the shamans and the priests who were also the medicine men and women. Unfortunately, during those ‘dark ages’ attempts at pain relief focused more on the exorcising of the evil spirits from the body and not so much relieving the discomfort (Olson, 2013). The ceremonies involved a combination of magical and religious rituals that included incantations, scarifications, and the application of various pumice, bloodletting, vomiting (Colliers, 2018). Regrettably some of these

rituals are still practiced in remotes parts of the world, with the same of the same results, namely continued agony for the sufferer.

Across the globe, history of pain has been marked with very little understanding of the cause of pain but with prodigious attempts to alleviate it. As time progressed, beliefs about ideas of pain evolved slightly from demon possession to that of the evitable suffering of the soul, brought on by the sinful nature of all ‘fallen beings’ (Sabatowski, Schafer, Kasper, Brunsch, & Radbruch, 2004). Pain was regarded as Divine justice and any effort made to alleviate it was considered interfering with the will of God. But this view of the inevitability of suffering was not held by everyone and there was ongoing exploration into the various methods of relieving pain. These early research into pain relief coincided with the birth of the first modern-day medical schools in Europe organized for training physicians and standardizing the practice of medicine.

Interestingly, more than half of the formulations documented at these then new medical schools were for the treatment of pain (Sabatowski et al., 2004). These potions were mostly anesthetic in their effect and were used for surgical procedures such as amputations and trepanning (drilling into the skull). The most effective of these potions were the Laudanum- a solution of opium mixed with alcohol that allowed for controlled and standardized administration of the drug for various ailments. The invention of this tincture proved to be one of the most monumental invention in the practice of medicine up to that time (Sabatowski et al., 2004). But even then, its use was not without the warning of potential of addiction, and the religious community was still opposed the administration of any unholy drug with a conscious altering effect.

Pain during the Renaissance. The renaissance marked the rebirth of science and inquiry in the practice of medicine. Humorism, though an ancient ideology created by the Ancient Egyptians and promoted by Hippocrates, was popular once again. Humorists believed in the holistic working of the body and that one's health and temperament controlled by the four humors. Accordingly, pain, like all other disease conditions, was thought to be the imbalance of the four humors of the body: blood, phlegm, yellow bile and black bile (Germossa, 2018; Meldrum, 2003). Medicine and pain relief was the art of balancing the humors and this required the administration of oral medication that was usually a mixture of opium, other herbs and an alcoholic brew of some kind (Meldrum, 2003).

Fortunately, it was also during the renaissance that researchers were uncovering the anatomy of the living creatures, including the human body. This led to increase understand of pain and the role of the brain and nervous system in pain perception and sensation. The then medical community was realizing that there was both a physical and a mental aspect to pain and that treatment should include a focus on both (Olson, 2013). The diagnostic value of pain was also becoming increasingly accepted in the practice of medicine. But it would decades before the true importance of pain would be appreciated and the treatment of pain would be an independent specialty in medicine.

The 17th century saw major advancement of all forms science and especially in the areas of medicine and human biology. The prevailing understanding of physiology was the perception of the human body as a machine that was made up of fluids and solids. It was Descartes, the French philosopher, who put forth the idea that pain

transmission was the blocks in the flow of the fluids of the system of nerves that ran the machine (Germossa, 2018). Treating this pain therefore required the use of gases such as nitric oxide or ethers, or solutions of alcohols that caused the fluids to resume their continuous movement. Incidentally, at the end of the century a London doctor, Dr. James Moore, was rediscovering the use of opium, as an effective post-operative pain relief (Sabatowski et al., 2004). Meanwhile, Dr. Mesmer, a German doctor, was popularizing the hypnotic effect of mesmerization, and in Holland, Dutch doctors were introducing acupuncture (needling) and moxibustion (cupping), learned from their Japanese colonies, as effective pain therapy (Sabatowski et al., 2004). Pain therapy was rapidly advancing and brought comfort to many and facilitated medicine becoming less of an art and more of a science.

Pain in recent history. By the beginning of the 19th century, pain was no longer regarded as demon possession or as punishment for sin or as an imbalance of the humors. These old ideas were all replaced by the new physiology of pain and the generation of pain sensations. The advancement in technology provided additional insight into the pain mechanism that positively affected the success of the pain intervention efforts. Extensive research in the area increased the knowledge of the sensory organs and the pain pathway and its role in the underlying illnesses. If pain was a sign of disease, then that disease could be discovered, and the cause treated, and the pain alleviated. This era was also marked by new insight into the nociception, the response of the CNS to painful stimuli. And in a lab in John Hopkins, Dr. Candace Perth was the discovering the opioid receptor (on the cell membrane) as the docking point for all the opioid molecules that initiates the

euphoric and analgesic effects of the drug (Pert & Snyder, 1976). But before these findings could bear fruit, the theories of pain and the drugs used in the treatment of pain would go through several ideological revolutions.

The Modern Era of Pain Management

New theories of pain management. Managing patients' pain is a vital component of providing valued health care as it is essential to any quality of life measures. As a disease, chronic pain requires an approach to the biological, psychological, personal and social aspects, making a solution challenging (Mills, Torrance, & Smith, 2016). Dealing with chronic pain is common to many medical cases, with over 70% of cancer patients experiencing moderate to severe pain and (Reis-Pina, Lawlor, & Barbosa, 2015). Also approximately 88% of patients who are dealing with other chronic illnesses, such as cardiovascular disease, arthritis, and chronic obstructive pulmonary disease (COPD), also experience chronic pain as their most common comorbidity (Mills et al., 2016). However, pain management remains complicated by the subjectivity of pain measures and the need to balance the patients' rights to pain relief and the risks involved in administering analgesics. But as much as pain is common to all sentient beings, relief from pain and suffering is a cardinal principle underlying any effort towards health and healing (Committee on Advancing Pain Research, Care, 2011).

The modern era marked the emergence of several theories to explain the nature of pain and to guide treatment modalities. The first pain theory came in 1958 and was known as the "Specific Theory," suggesting that different types of pain had very different sensory processes, each with a very specific peripheral pathway (Meldrum, 2003). This

theory did not foster much success in the realm of pain treatment however, and it was soon replaced by the “Gate-Central Theory” that sought to improve on the clinical and psychological treatment of pain (Mills et al., 2016). The “Gate-Central Theory” theory taught that even though pain had a peripheral origin, the perception of the sensation was governed by a control trigger that was centrally located at the level of the Central Nervous System. This theory facilitated the birth of several modalities such as the transcutaneous electrical nerve stimulation (TENS). TENS along with massage therapy, the application of pressure, and or electrical stimulation all proved successful in treating various pain-related ailment (Mills et al., 2016).

Pain management as a field in medicine. By the 1960s attempts to officially form a new ‘Pain Management’ genre in the medicine was growing among the healthcare professionals in the field. But this would not come until the 1970s, with the formation of the International Association of the Study of Pain (IASP) and the launch of the journal *Pain* (Colliers, 2018). First the IASP was focused on establishing interdisciplinary teams responsible for treating patients presenting with chronic pain. This patient-centered, clinic team approach to pain proved successful by patient satisfaction reports but it would be short lived. Unfortunately, the team approach did not survive because these pain clinics were too expensive for the parent institutions to support, were too complicated to bill for reimbursement, and were generally looked upon unfavorably by the insurance companies (Colliers, 2018). Additionally, there was no backing from the rest of the medical community as far as educating and training student doctors to perform as a member of such a team (Colliers, 2018). Consequently, the team approach to pain management

dissolved and regrettably the field reverted to the singular physician approach.

Chronic pain continued to widely recognized as a major medical and public health issue, affecting 100 million Americans and costing an estimated \$635 billion a year in treatment and productivity lost (Committee on Advancing Pain Research, Care, 2011; Nahin, 2015). But ‘Pain Medicine’ or Algiatry only become its own specialty in the last decade or so and the several newly established professional organizations provided inadequate training guidelines and inconsistent response to the increased demand for related treatment service (Dubois & Follett, 2014). Over the years the effort at providing effective pain management therapies have led to new policies, but there still exists a significant gap between the policy and the practice in the field (Reis-Pina et al., 2015). The shortfalls in pain assessment and treatment are the result of outdated policies, inadequate treatment guidelines, insufficient provider training, lack of research and provider bias and unhelpful attitudes (Committee on Advancing Pain Research, Care, 2011). Addressing gap has been an area of focus for many years and remains a challenge for policy makers and health care professionals today.

Even though, the interdisciplinary teams of pain therapy were done away with, the IASP survived and they continued to work towards improving the healthcare response to pain. Pain Management now and official specialty, was a relatively new area of medicine and was tasked with establishing standardization of the pain therapy and analgesic administration (Tompkins et al., 2017). The work of the IASP and other organization like it generated increased research into the pathophysiology of pain. Pain would be officially defined as “an unpleasant sensory or emotional experience associated actual or potential

tissue damage or described in terms of damage” (Colliers, 2018). And any pain experience that lasted beyond the normal healing phase, which was usually under three months, and was not associated with a chronic illness, was considered chronic (Cheung et al., 2014).

The search for the perfect painkiller. While the field pain and pain physiology were advancing, a related development was happening in the world of the substance used for pain relief. Opium, the product of the poppy seed, known to be effective for pain for centuries, was becoming the go to drug. Opium in various forms was seen as the universal panacea and was used for everything from headaches, to small pox, to fever to upset stomach. Instead of being smoked, opium was now eaten as a solid or drunk as the solution Laudanum (Meldrum, 2003). Laudanum was a mixture of opium combined cinnamon, saffron, cloves, all dissolved in wine. This solution made the administration of exact dosage of the drug possible and therefore more convenient to use regularly and was almost extensively among the upper class, while the lower class would line up to purchase the now more affordable over the counter pill-form (Meldrum, 2003). The prevalent use of opioid, in either formulation, was fast creating the problem of increasing dependence and addiction in the Western hemisphere as it had been for China and the Eastern hemisphere in the previous century.

While the widespread use of opium and its accompanying addiction was deemed problematic, the effectiveness of opioid as a pain relief could not be denied. The issue for researchers was how could the benefits of the drug be retained but without the addicting side effects. Concerted effort resulted in chemists isolating the sleep inducing agent from

the poppy seeds at the beginning of the 19th century and the new formula was called morphine after Morpheus the Greek god of sleep (Reis-Pina et al., 2015). Concurrent with this discovery, the invention of the hypodermic syringe and needle allowed morphine's subcutaneous administration (Meldrum, 2003). This subcutaneous form was distinguished from the orally administered, extremely addicting form. But the positive estimations were short lived as morphine proved to be just as or even more addictive than other forms of opioid (Meldrum, 2003). The researchers remained optimistic however, that a non-addicting form of opioid could be extracted, and the enquiry continued.

The research to find a non-addicting, pain-relieving opium derivative received added impetus from the many regional and international wars taking place at the time. The growing number of injured soldiers from the American Civil and other wars in Europe saw many of them become addicted to morphine (Berridge, 2009; Meldrum, 2003) this loss of vitality and productivity, and in some cases loss of life that morphine addiction brought to thousands of young men was a serious problem that needed a solution. It was in 1865 that the Bayer Company in Germany discovered the diacetylmorphine formula that they patented with the name 'heroin' (Cicero, Ellis, Surratt, & Kurtz, 2014). Like morphine, heroin was believed to be less addictive than morphine and more effective than the opiate-based cough suppressant codeine. Unfortunately, as use of this new formulation would reveal in time, this over the counter form of the drug, even though a less powerful analgesic than opium, it was potentially even more addicting than all previous forms (Lembke, 2016).

The mixed success of heroin did not dampen the research efforts to find a non-addicting formulation of opium that was just as effective at pain relief. This led to the proliferation of many semi-synthetic and synthetic versions onto the market. In the middle of the century, with lots of WWII German soldiers needing relief from their war injuries, the effectiveness of the synthetic opioid, methadone was discovered. Originally, German scientists created methadone to make up for the short supply of opium during the war. As if by fortune, anecdotal evidence pointed to methadone's long half-life and sustained analgesic effect, that somehow appeared to suppress cravings and feelings of addiction ("Methadone | CESAR," n.d.; Sabatowski et al., 2004). This eventually led to methadone becoming the ultimate antidote to help patients successfully endure heroin withdrawal during treatment for addiction. The popularity of methadone use grew and so did use of the methadone maintenance therapy in clinics across the U.S (Hall & Strang, 2017; Sabatowski et al., 2004). The effectiveness of methadone and its partial success in pain therapy and addiction management drove the research into synthetic opiates. Meperidine or Pethidine (known commercially as Demerol) was another synthetic opioid created in 1939 by German Chemist, Otto Eisleb (Meldrum, 2003; Yasaei & Saadabadi, 2018). His research revealed that meperidine had analgesic properties and was versatile in its administration properties. Whether in a syrup solution, as a subcutaneous injection or intravenously, meperidine became the most popular choice for physicians in the mid-1970s, as they prescribed it for both acute and severe pain (Manchikanti et al., 2012). At that time, they believed meperidine to be less addictive and thus safer than morphine, but again, later evidence pointed to the dangers of long-term use. Meperidine would become

known to be more toxic and in 2003, it was removed from the WHO List of Essential Medicines, but alarmingly, it remains the most widely used opioid analgesic during labor and delivery (Yasaei & Saadabadi, 2018).

Fentanyl, another synthetic opioid, was the next opium option on the market, created by an American chemist Paul Janssen in 1960s (Stanley, 2014). Fentanyl is widely used legally in healthcare for both analgesic and anesthetic purposes, but it is also very popular as an illegal, recreational drug. It is 100 times more powerful than morphine and is currently the most widely used of all the synthetic opioids, while many of the illegally produced analogues are 100 times stronger than fentanyl itself (Paparella, 2014). Fentanyl can be administered in many forms, including intravenously and intrathecally. Intravenously it is mixed with either propofol for general anesthesia, or benzodiazepine during oral surgery or endoscopy. Alone it is used in the treatment of chronic pain such as that of cancer patients or chronic low back pain. Intrathecally, fentanyl's chemical properties make it a suitable for epidurals, as well as transdermally, in time-release skin patches (Paparella, 2014). Orally, as sublingual lozenges (Oral Transmucosal Fentanyl Citrate or OTFC) or as lollipops, or nasally, as sprays or inhalers are other modes by which this drug can be administered (Paparella, 2014).

Unfortunately, the pharmaceutical fentanyl is one of the opiates that finds its way onto the black market and combined with the illegal manufacture and distributions of the analogues, makes it a major public health nightmare. Fentanyl can be smoked, snorted, injected or ingested and because of the similarity of its effects to heroin, it is sold, deceptively as heroin or oxycodone, but is so much more lethal (Stanley, 2014). The

FDA issues warnings in 2005 and again in 2007 public health advisory, warning about the dangers of Fentanyl use, particularly the patches, which “doctors were inappropriately prescribing, and patients were incorrectly using” (Stanley, 2014). During that time, the Insurance Company attempted to respond to this national public health crisis by requiring physicians to have precertification and instituting limits on the quantity they could prescribe. However, the situation persisted and in 2016, 20,100 persons (half of opioid related deaths) died from an overdose of fentanyl, which was a 540% increase from the number in 2013 (Manchikanti et al., 2012).

Other semi-synthetic opioids were continually being placed on the market. Oxycodone or oxycontin (known commercially as Percocet), can be administered as an immediate release or controlled release, intramuscularly or intravenously, combined with paracetamol (acetaminophen) or and with the nonsteroidal anti-inflammatory drugs (NSAIDs), aspirin or ibuprofen (Mazer-Amirshahi et al., 2016). Oxycodone, like the many opioid alkaloid, is derived from the opium poppy seed, and was synthesized in the 1917 in Germany after Bayer had stopped producing heroin. It is created by industrial conversion from thebaine, an opiate alkaloid, and acts as a moderately analgesic, slightly more potent than morphine and due to its mild euphoric effect, it is one of the drugs contributing to the opioid abuse epidemic (Puja Seth, Rudd, et al., 2018). Other forms of opioid include codeine, the popular pain killer and cough suppressant, as well as hydromorphone, buprenorphine, hydrocodone, and hydromorphone.

As the research were going on laboratories across the world to find the best chemical compound that could relieve pain and was not addicting, others were trying

something different. Much of the earliest history of pain relief is closely tied to use of opium as it served as both as a psychoactive effect and the analgesic properties. Other non-opioid pain-killers included ether, chloroform, used extensively during childbirth and for dental surgeries in the 1800s (Meldrum, 2003). In the early 1900s, morphine and heroin were believed to be the answer to the pain dilemma as it seemed to relieve pain, improve the patients' quality of life, while not present any apparent side effects. But those side effects were showing up and the picture was gloom. There was the suppression of respiratory activity, the mental depression and low mood and with extend use came the abuse and addiction. But opium was always remained at the forefront and has caused a concerted effort to maximize its potential for good while minimizing it's the risk of its side effects.

How opioids became the drug of choice. The field of pain management has undergone several changes over the years and the relief of pain has evolved. The changes have been driven by the need to find better solutions that meet the needs of patients and help the healthcare workers be more confident in administering them. In the early 1990s, there were reports of inadequate pain management and unnecessary suffering caused by under-treatment of patients' pain and this prompted a review of the practices followed by changes in pain management policies (Agency for Health Care Policy and Research, 1992; Dubois & Follett, 2014; Mills et al., 2016). To curtail the reports of under-treatment, more proactive measures in pain treatment were instituted as the existing procedures were deemed not effective enough (Cheatle, 2015). This lead to the replacement of the paracetamol (acetaminophen) and non-steroidal anti-inflammatory

drugs (NSAIDs) with the controversial opioid based analgesics (Morone & Weiner, 2013).

Despite the history of addiction risk associated with opioid, its use as the go-to prescription drug in pain management was growing. The idea of possible under-treatment combined with the new more effective, faster-acting opioid drugs and the aggressive marketing by the pharmaceutical companies resulted in physicians replacing their opioid phobia with an over confidence in the drug (Kata et al., 2018). A few experts were touting opioids as safe and non-addicting and the physicians were prescribing them major doses of them to everyone who complained of pain (Daum, Berkowitz, & Renner, 2015). The newer longer-acting opioid formulations with improved bioavailability and aggressive marketing by the pharmaceuticals, led physicians to give up their opioid phobia and replace it with a less restrained prescribing habits (Sehgal, Manchikanti, & Smith, 2012). Although not much was known about the risk involved in long-term use of opioids or the adverse effects of heavy dosages, the drugs proved effective and this combined with other patient and physician factors resulted in increased opioid prescriptions being dispensed (Juurlink & Dhalla, 2012). The situation soon resulted in a dramatic upsurge in opioid prescriptions, with the rate doubling twice by the end of the decade (Cheatle, 2015). But this development did not happen in a vacuum and other changes in the field would precipitate the opioid epidemic.

Pain as a fifth vital sign. It was during the changes in drug choice, that another important policy regarding pain management was taking place. In the 1995, the American Pain Society was successful in getting “pain” to be classified as another of the vital sign that should be routinely monitored in a medical setting (Morone & Weiner, 2013; Seden, 2015). Pain became the 5th vital sign, after “body temperature”, “pulse rate”, “respiration rate (rate of breathing)”, and “blood pressure”. As a result, pain reporting became more common, and this drove the increased prescription of analgesics. One of those landmark changes was the declaring of pain as the 5th vital sign. Unfortunately, making pain a 5th vital sign had some negative consequences. The Numeric Rating Scale (NRS) was being used to report the level of pain patients were experiencing. However, these patients were reporting pain because they had to, even when there was no real suffering being endured as a result of it (Morone & Weiner, 2013). Additionally, the medical professionals were not adequately trained nor were they offered sufficient face-to-face time to properly assess the nuances of the pain that the patients were reporting (Morone & Weiner, 2013).

Making pain the fifth vital sign was yet another factor driving the increased rate of opioid prescription. In addition to the NRS which measures the severity of sensation, pain can be classified based on additional features such as frequency of occurrence, duration of discomfort, response to treatment or other changes, and the presence of any incapacitating consequences (Committee on Advancing Pain Research, Care, 2011). The distinction between acute pain and chronic pain was being blurred and while acute pain is a vital sign, chronic pain is its own distinct entity. Other important distinctions were

overlooked, such as whether the pain was nociceptive (tissue damage) or neuropathic (nerve damage), which each require a different treatment approach (Mills et al., 2016).

According to the International Association for the Study of Pain (IASP), the focus is on the cause when dealing with acute pain, but for chronic pain it is all about the reducing the effect and improving quality of life (Mills et al., 2016). But physicians, pressed for time, resorted to ubiquitous opioid prescription for anyone reporting pain symptoms. This behavior only added to the growing problem of an overabundance of opioid prescription and a subsequent increase in opioid abuse and addiction.

In 2000, the new pain management laws put in place by The Joint Commission: Accreditation, Health Care, Certification (TJC) reinforced the right of each individual to pain relief and the obligation of doctors to administer pain medication to patients presenting with pain complaints (Manchikanti et al., 2012). The facilitated increase support for not for the use of opioids but for the use of large doses. This also motivated the aggressive marketing of the drugs along with misinformation about their efficacy and safety. This led to dangerous assumptions on the part of prescribing physicians and perilous situations for patients being treated.

The next decade saw the rise in the use of prescription opioids as they were now believed to be safe as there was little research and therefore little evidence of its addictive propensity. In the age of the “prescription culture” where drugs were seen as *the* solution to most medical issues, opioid became more popular among oncologists in the long-term treatment of cancer patients’ pain as well as others suffering from moderate and severe chronic pain episodes (Colliers, 2018). This rise was driven by the heavy campaigning of

the pharmaceutical companies that lasted almost two decades. Opioids were not only promoted as safe and effective, they were promoted as have a high cost-benefit ratio for the patients, an idea endorsed by the major insurance carriers. Exacerbating the epidemic of opioid use was the work of drug-traffickers who were able to traffic cheap versions of the drug and their many analogues. The effect of making pain the 5th vital sign combined with the other negative forces in the society at the time conspired to exacerbate the brewing opioid addiction crises.

Drug Addiction and the Opioid Epidemic

The birth of the opioid epidemic. The turn of the century saw opioids becoming the most common analgesics in pain management therapy, sustained by their effectiveness in treating all types of pain. Opioid is an effective analgesic that also produces the mind-altering effect of euphoria and it is this effect that can lead to addiction and abuse. People start off using the drug for relief from pain, but eventually continue after the pain is gone— because of compulsion; seeking feelings of reward; or for diversion from their life (Gugelmann, Shofer, Meisel, & Perrone, 2013; Murthy, 2016). In most cases the illicit use of the drug started with a prescription for a non-cancer related pain, usually a high-dosage prescription of an extend release version of the drug (Sehgal et al., 2012). This unfettered prescribing, despite the absence of evidence of its long-term effectiveness and conflicting physicians' guidelines, resulted in many cases of opioid misuse and abuse (Cheatle, 2015; Manchikanti et al., 2012).

Over the last two decades, the frequent and wide spread use of opioid drugs caused many to ignore the emerging signs of adverse effects and to falsely believe in its

safety at any dosage. By the year 2003, prescription drugs abuse, a majority of which involved opioids, was now greater than that for illicit drugs like, methamphetamine, cocaine and heroin (International Narcotics Control Board, 2006). Later research on the efficacy and risks involved in long-term use would report on— the potential for adverse effects, the low to moderate effectiveness, and the increased probability of overdose as well as the abuse associated with prescriptions for high dosage and long-term use of these drugs (Cheatle, 2015). But in the meantime, many physicians were finding opioid prescribing to be a quick and convenient solution to the many challenges faced in the field of pain management (Lembke, 2016).

By 2010, opioids, which were previously restricted to use for severe or chronic pain, was now used for all types of pain regardless of intensity or duration. Opioid prescriptions were first introduced for the treatment of the severe pain associated with major surgery or trauma, but now it had become the mainstay for other pain symptoms as well (Reis-Pina et al., 2015). But now doctors everywhere were prescribing high doses of opioid for long-term use in the treatment of severe as well as moderate pain, but there was little knowledge about the actual threshold for these drugs or the risks involved in going beyond said threshold (Cheatle, 2015). The rise in the rate of opioid prescription and the sale of the opioid pharmaceuticals would see an increase of 400% between 1999 and 2010 (CDC, 2011). It is the excessive prescription of opioids, in the form of chronic opioid therapy (COT) and for chronic non-cancer pain (CNCP), that led to the explosion of opioid addiction and the many ill effects in the society. The increase in long-term opioid use and COT together with the liberalizing of the laws governing its use in NCP

over the turn of the century culminated in an increase in abuse, addiction and death from the misuse of the drug (Cheung et al., 2014). This errant prescription behavior fueled by a lack of knowledge and a dearth of education or training was believed to be the “root cause of the opioid epidemic” was to taking hold among the community (Barnett et al., 2017).

The challenge of defining drug addiction. Documenting the extent of the opioid epidemic has always been complicated by the absence of any universally accepted characterization for addiction. Those attempting to measure the prevalence of abuse and addiction of any analgesic has had many trials, as standardizing a diagnosis of abuse or even misuse in field of pain management is almost impossible, even for the pain experts (Mills et al., 2016). The lack of diagnosing regulations along with the inconsistency in defining abuse, results in challenges to measuring the extent of the problem (Sehgal et al., 2012). This lack of uniformity is reflected in the reports of rates of abuse, varying from 1% to as much as 40% across different research findings (Cheatle, 2015). A lot of work has gone into documenting and reporting on the epidemiology of the opioid epidemic, and much has been reported but some uncertainty remains.

In an attempt to resolve the uncertainty relative to diagnosing addiction, several agencies got involved. At the beginning of 2001, the American Pain Society (APS), the Society of Addiction Medicine (SAM), and the American Academy of Pain Medicine (AAPM) joined forces to develop a much-needed working definition for addiction, for those in the pain management community. This group defined ‘addiction’ based on various signs including- subjects inability to control their use of the drug; continued use

even after the drug causes obvious harm to the user; using the drug compulsively; and craving the drug for reasons other than to relieve pain (Cheatle, 2015; Sehgal et al., 2012). But this did not simply things, as all the signs can also be seen patients dealing with other physical ailments and comorbidities other than those for which they were prescribed analgesics (Von Korff et al., 2016). This combined with the issue of drug tolerance and drug dependence being common in normal pain management therapy makes any official diagnosis abuse and addiction difficult (Hughes et al., 2016).

Other agencies, recognizing the need for standardization, decided to join in the effort to try and formalize a definition for addiction. The Analgesic, Anesthetic and Addiction Clinical Trials, Translations, Innovations, Opportunities and Networks (ACTION), panel of experts in the field, came together to put forth recommendations for defining abuse and monitoring prescriptions. In their published report, inappropriate use of the drug was defined as misuse and abuse was defined as intentional use of the drugs for the psychological effect (Cheatle, 2015; Han et al., 2017; Vowles, 2015). Additionally, the Statistical Manual of Mental Disorders (DSM)-Fourth Edition included tolerance and dependence along with the behavioral abnormalities in their definition of chronic opioid use (Sehgal et al., 2012). But the 2013 version of the DSM-Fifth Edition changed the Substance Use Disorder category supposedly to simplify diagnosing abuse. The DSM combined abuse and dependence into one and this new category had three levels of severity- mild, moderate and severe (DSM-5 quoted in Cheatle, 2015). They then made tolerance and withdrawal relevant only in the cases where there was no licensed clinician, but this did not simply the issue. The DSM-IV version of abuse

includes the terms ‘tolerance’ and ‘physical dependence’, both of which are inevitable consequences of chronic opioid use. The APS definition ‘compulsion’ and ‘craving’, which are also difficult to assess as they can be caused by real underlying need for pain relief (Sehgal et al., 2012). There were now several working explanations but no universally accepted definition of addiction.

The many editions issued as the definition of pain by the pain ‘experts’ proved counter to the needs of those dealing with patients as well as those attempting to document the extent of the problem. For example, the rate of abuse based on the more sensitive DSM-5 did not differ much from that using DSM-4, and the rate of misuse and abuse from systematic reviews of several studies, using ACTION guidelines, varied between 1 and 81% across 38 studies (Cheatle, 2015). Although these studies included a variety of clinical settings, different patient populations, and an assortment of pain conditions, the variation indicated the need for additional work on the consistency of the approach. Insufficient or inadequate standardizing of abuse and addiction definitions made determination of prevalence among patient population a persistent issue. This discordance makes it challenging for healthcare providers and regulatory forces to come to a consensus on the nature and extent of the problem. To devise appropriate treatment plans to deal with the disorder of addiction and reduce the burden on the society better standards based on evidence-based research is needed (Murthy, 2016). Despite the lack of precision to the existing data, the opioid epidemic is real and that it demands a solution.

The height of the opioid epidemic. Despite the inaccuracies, there are many estimates that provided an insight into the extent of the developing opioid epidemic. At the beginning of the decade there were 15.3 million adult Americans using opioids, and that number would rise to 23.8 million in 2005 (Sites, Beach, & Davis, 2014). Over the five-year period from 2006 to 2011, morphine use went from 1.82 mg/person to 61.66 mg/person (Cheung et al., 2014). The true incidence was believed to be higher, but an estimated 26% of the COT outpatients and 20% of Medicaid patients were abusing opioids (Sehgal et al., 2012). The prevalence of opioid abuse went from 4.1% to 4.6% among young adults during the years 2002 to 2007, with overdose fatalities at 15.9% for males and 11.2% for females (Rudd, Aleshire, Zibbell, & Gladden, 2016). By 2009, there were over 7.0 million (approximately, 2.8% of the population) addicted to opioids and this was an increase from the 6.2 million counted in 2008 (Sehgal et al., 2012). In 2010, 60% of all drug overdoses were from prescription drug and 75% of those were opioid analgesics (National Survey on Drug Use and Health, 2013). The problem of opioid abuse was growing, fueled by the growing rate of opioid prescriptions being dispensed.

As rate of opioid prescriptions escalated, rate of abuse of the drug continued to rise. This reflected an increase in the number of medical emergencies related to prescription drug abuse by 183% from 2004 to 2011 (U.S. Department of Health and Human Services, 2013). By 2012 there were 4.9 million users reported abusing opioids, while some 35% of those in chronic opioid therapy eventually developing an opioid use disorder (Cheatle, 2015). That same year 488,004 patients presented to the emergency room (ER) with opioid overdose and another 180,004 were treated for using opioid for

non-medical reasons (Cheatle, 2015). Moreover, the abuse of prescription drugs is also tied to other drug use, as one study found that 80% of all heroin users previously used prescription medication (Muhuri, Gfroerer, & Davies, 2013). In 2015, the National Survey on Drug Use and Health (NSDUH) survey determined that prescription psychotherapeutic drugs, mainly opioids, were second only to marijuana as the most prevalent illicit drug (Hughes et al., 2016). The opioid epidemic was exploding in the society and it was contributing to other issues of drug abuse.

The opioids involved in opioid abuse had some distinct characteristics. The extended release and the immediate release forms of hydrocodone and the oxycodone account for 75% of the abused prescription drugs (Hughes et al., 2016). Fentanyl, hydromorphone and morphine, the more potent μ -opioids, made only a small portion (5%) and methadone was the street drug of choice in over 70% of the case, versus the 30% divided among OxyContin or Vicodin or Percocet (Sehgal et al., 2012). The sale of morphine increased by 222% and that of methadone by 1293% between 1997 and 2007 (Manchikanti et al., 2012). Unfortunately, almost a decade ago, the reports already indicated that Americans use 66% of all the illegal drugs on the planet, consuming 80% of all the opioids and 99% of all hydrocodone (Manchikanti et al., 2007). Untangling the web of opioid drugs is one of the most difficult aspects of this epidemic.

Added to the many problems caused by the opioid epidemic is that of drug diversion. Much of the drugs being abused are obtained originally from a prescription but ends in the hands of friends or relatives for whom it was not prescribed. Over 56% of all opioids used non-medically and 50% of all used in the overdose fatalities are classified as

diverted drugs (Sehgal, 2002). These are obtained from elderly pain patients, from those who engage in doctor shopping or bought illegally on the black market. Unfortunately, the abuse of prescription opioids is considered the gateway to other drug addiction, namely heroin (Beaudoin et al., 2018; Murthy, 2016; Poon & Greenwood-Ericksen, 2014). Opioid abuse is linked to other illegal drugs as well as the use of legal drugs like cigarettes and alcohol, all of which makes it difficult to design dissect the problem and design interventions.

The burden of the opioid epidemic. Opioid abuse was causing a great deal of health problems and this took an exorbitant toll on the cost of health care. A patient who was also an opioid abuser was costing 1.8 times that of a non-abuser, \$16,000 versus \$1,800 and the total cost of the opioid epidemic in 2001 was \$8.6 Billion in healthcare cost, work place earning lost and the criminal justice system expenditure (Sehgal et al., 2012). By 2007, the cost was \$55.7 Billion and the annual cost for each opioid abuser was now \$20,546 (Meyer, Patel, Rattana, Quock, & Mody, 2014). There is also the disability cost associated with opioid abuse as chronic opioid therapy (COT) is associated with an increase in disability and added financial expenditures. The cost of care for patients using the opioids are three times more likely to need surgery and on average require 69 more days of disability and workers compensation than those not using opioid (National Academies of Sciences, Engineering, and Medicine, 2017; Florence, Luo, Xu, & Zhou, 2016). Both opioid use and opioid abuse was costly to the society and to the healthcare budget.

In addition to the financial burden of the opioid epidemic, there were certain more direct dangers associated with the use of these drugs. Opioids can cause opioid-induced hyperalgesia (OIH), a condition of patient becomes even more sensitive to the painful stimuli and experiences more painful sensation when taking the medication than when not taking it (Cheung, 2014). Opioids are also known to cause respiratory depression or hypoventilation, which can result in respiratory arrest and eventually death if not treated in time (Reis-Pina et al., 2015). Opioids are also associated with an increase in suicide rate, increase in overdose, increase in crime rate to users (National Center for Health Statistics, 2015a). While opioids are an important and effective analgesic but there are many dangers associated with this class of drugs, unfortunately the former is better known than the later.

Opioid-related morbidity and mortality. Poisoning is the leading cause of injury death, and 90% of these poisonings are from the misuse/abuse of prescription drugs, mainly opioid pain relievers (OPR) (National Center for Health Statistics, 2015a). Between the years 1999 -2011, the opioid prescription related (OPR) deaths almost quadrupled, going from 1.4 to 5.4/100,000, and although the rate slowed around 2006, it started rising again in 2011 (Cheatle, 2015). The increase in OPR death rate was seen across all age, all racial groups, and urban areas in multiple states, accounting for two thirds of drug overdose death (Seth, Scholl, Rudd, & Bacon, 2018). States like NH, OH, WV had the highest death rates, some prescription OPR deaths higher than that for heroin (Vivolo-Kantor et al., 2016). The first wave of prescription OPR deaths occurred in 1990, the second in 2010 with mostly heroin deaths, and the third wave in 2013, mainly from

the synthetic opioid illicitly manufactured fentanyl (IMF) (Vivolo-Kantor et al., 2016). The IMF accounted for 30.5% of all drug overdose deaths and 45.9% of all OPR deaths, representing a 100% increase from 2015 (Seth et al., 2018). Figure 4 includes comparative data on drug overdose deaths overall and deaths specifically involving opioids.

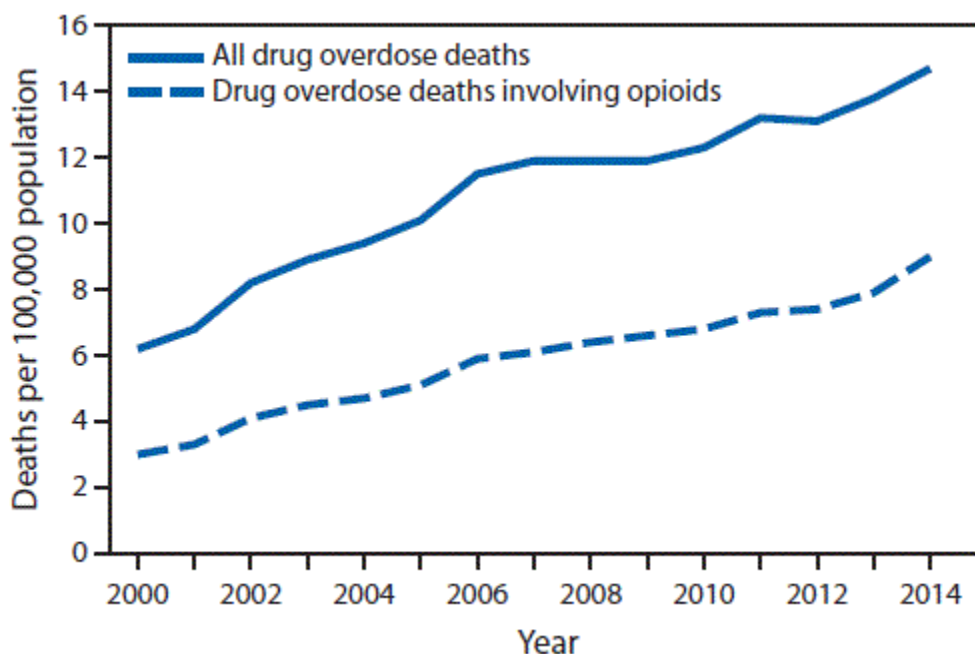


Figure 4. Drug overdose deaths (P Seth, Scholl, Rudd, & Bacon, 2018).

The epidemic of drug overdose is growing, and this is evidenced by not just the worsening opioid-related death rate but specifically the deaths from opioid analgesics (OA) overdose. Like the increase in opioid prescriptions, deaths caused by unintentional prescription opioid overdose has risen sharply over the past two decades and have surpassed deaths from heroin and cocaine combined (Substance Abuse and Mental Health Services Administration, 2016). The rate of drug overdose increased 137%, and 200% for OA overdose, including natural and semisynthetic opioids (Rudd, 2016).

Between 2013-2014, the age-adjusted increase for natural and semisynthetic OA, heroin, synthetic OA (fentanyl) OA were 9%, 26%, 80% increase, respectively (Rudd, Seth, et al., 2016). Over half a million died from opioid overdose between 2010 and 2014, mainly opioids (prescription pain reliever and heroin), but 61% died 2014 alone making it the deadliest year since (Rudd, Seth, et al., 2016). Unfortunately, of the 63 632 persons who died of drug overdose in 2016, 66.4% were OA overdose, most of which were IMFs (Seth, 2017). The increase in prescription OPR and the surge in IMF availability, contributes to this growing dilemma that continues unabated despite many intervention strategies.

In the past, reports of deaths caused by an opioid overdose usually include both prescription opioids and illicit opioids, thereby inflating the reports with no distinction made between the sources in the death certificates or the coroners' reports. For example, in 2016, that number was 42,249 and included morphine and oxycodone (prescription) and heroin (illicitly manufactured fentanyl or IMF and heroin), but half of which was believed to involved IMF (Seth, Rudd, Noonan, & Haegerich, 2018). Combining the numbers hid the fact that the prescription drug-related deaths had not changed much, and the increase was mainly due to the sharp increase in the use of synthetic opioids, mostly IMF (both prescription and illegal manufacture). However, new procedures put in place by the CDC allows for improved distinction between the prescription and the illicit drugs involved in overdose fatalities (Seth et al., 2018). Effective prevention strategies depend on accurate targeting of the correct source of the problem, e.g., high-risk prescribing vs illicit drug availability. It is believed that educational guidelines and prescription

monitoring as well as stricter enforcement are an integral part of solving the epidemic. Partnership between public health, medicine and law enforcement are all essential to the success of the response.

Screening and the opioid abuse risk factors. Identifying the risk factors associated with potentially abusing opioid or developing an addiction to the opioids is critical to the response to this public health dilemma. Although there are many screening tools, their use is not mandatory, and none have been validated for generalizable use across different sectors of the country. Most of the tools are made up of a paper survey to collect medical and personal history and a one-on-one interview to assess mental, physical and psychological state (National Center for Health Statistics, 2015a). The most recently published study that examined the link between ED prescription and opioid abuse was conducted using the database of a commercial insurer. Researchers wanted to do a comprehensive to study the factors that increase the risk of opioid abuse and dependence and used the database of a larger commercial insurer (Cochran et al., 2014). The study evaluated all the 2,841,793 patients who filed at least one opioid claim between 2000 and 2008, of which 2,913 were diagnosed with an opioid abuse disorder diagnosis within subsequent two years (Cochran et al., 2014). Young males who had a history of opioid prescription– combined with a history of psychiatric disorder (depression or anxiety), plus a lengthier prescription supply, who were also using other medications, and had used several pharmacies for filling their opioid prescriptions– were the ones more likely to develop an OUD (Cochran et al., 2014).

The collected patient data, along with the prescription guidelines, should be used to guide the providers' prescription decisions. This data collected should be used to assess the patients' suitability for opioid prescription and to determine the dosage. Subsequent follow-up assessments should be used to manage the patients' response to the medication and monitor any tolerance or dependence issues (National Center for Health Statistics, 2015a). The APS and the AAPM recommend a thorough history and physical exam and that the prescribing of opioid should be on a trial basis initially along with informed consent of the patient (National Academies of Sciences, Engineering, and Medicine, 2017). The dosage should be low to start, and the follow-up should consist of careful patient monitoring and any increase in dosage should be gradual dose titration (National Academies of Sciences, Engineering, and Medicine, 2017). But all these are recommendations and should be amended based on the unique situations that present and the skill of the provider of making the appropriate prescription response.

Using data from the published literature, researchers have attempted to classify the various risk factors involved in opioid overdose. Several factors have been identified and they include socioeconomic status, demographics, environmental factors (Beaudoin et al., 2018). Additionally, personal factors such as family history of drug abuse, genetics (the type of opioid receptor), history of alcohol and substance abuse, psychopathology and other pain tolerance and drug dependence factors (Pomerleau et al., 2016) (Weiner et al., 2013). Possession of any three, of the aforementioned risk factors, should be considered high risk for opioid abuse and care should be taken before prescribing opioid

to such a patient (Murthy, 2016). The factors and the associated screening tools are available, but their use is still not widespread.

One group of researchers undertook a systematic review of the literature to assess the major factors for opioid abuse across North America. The three main categories of risk they identified were: the behavior of the user; the patient's environment; and the behavior of the prescriber as having an influence on the rate of opioid-related mortality (King, Fraser, Boikos, Richardson, & Harper, 2014). Additionally, the role of the provider's prescribing pattern with respect to type of opioids (oxycodone, methadone, etc.), the dosage of the prescription, the duration of the prescription— were also key (King et al., 2014). The user-related factors included: how the opioids were obtained (diversion, pharmacy shopping, polydrug, etc.) and the patient's sociodemographic characteristics (race, gender, age, history of substance abuse). Rates of mortality were higher in non-Hispanic, White males, American Indian/Alaska natives and middle-aged persons living in rural areas (King, 2014). Even though other contributing environmental factors included SES, geography, PDMPs and policies and media coverage also played a role, race/ethnicity was determined to play a major role.

Most of the prescribing guidelines that were put in place at the height of the epidemic and some were more detailed than others. Physicians were advised to conduct a thorough personal history of the patient prior to prescribing any type of opioid. Knowledge of the patient's personal history, their family history, the criminal and incarceration history or any event triggering a post-traumatic stress disorder type reaction were deemed critical by some (Poon & Greenwood-Ericksen, 2014). Also important were

health issues such as whether they were smokers or alcoholics as co-occurring substance abuse was important (Sinnenberg et al., 2017).

Assessing the mental state of the patients is also very important as comorbid psychotherapy plays a role in addiction, as a history of mood disorder, depression and the use of psychiatric medication, all increase the patients drug misuse index (DMI) (Sehgal et al., 2012). Also common among abusers is a diagnosis of sexually transmitted diseases such as hepatitis A, B, or C or human immunodeficiency virus, acquired immunodeficiency syndrome (HIV) (“Opioids and methamphetamine: a tale of two crises,” 2018). These factors can be complicated by the patient’s level pain tolerance of the degree of personal impairment, limitation, or disability being caused by their pain (Reis-Pina et al., 2015). Though, this list is not exhaustive, but it demonstrates how many factors can play a role in a patient’s propensity towards abuse once prescribed an opioid.

Prescription Opioids and the Variation in Prescription Rate

The role of prescription opioids. Opioids, a type of analgesic made from the opium plants, and the prescription forms are the most powerful prescription for relieving pain. The prescription or legal opioids include hydrocodone, oxycodone and morphine and the illegal drugs include heroin and illicitly manufactured fentanyl (IMF). Although the prescription drugs are effective analgesic, they like the illegal ones, have psychotropic euphoria producing effects that can encourages physical dependence and possibly of addiction in some users (Sehgal et al., 2012). Use of these prescription opioids continue to increase despite the lack of supporting data and despite the increasing evidence about

opioid addiction and death due to over dose (Cheung et al., 2014). The increase in prescription opioid results increased exposure, it has been paralleled by an increase in opioid abuse.

An earlier study in Utah in 2011, was designed to investigate the role of prescription opioids in the opioid epidemic. The study was commissioned by the chief medical examiner to determine the extent to which prescription drug patterns of opioid played a role in the opioid crisis and whether the findings corroborated with the data from the medical examiner on death certificates (Porucznik et al., 2014). Medical records that included various administrative databases such as vital statistics, medical examiner records and emergency departments and state prescription registry were used (Porucznik et al., 2014). The researchers also intended to use the findings to design intervention programs that would help reduce the burden that the crisis was having on the state's medical care system. The analysis of the data, though possibly prejudiced by the data availability and ascertainment bias, confirmed the suspected link. The study found an increase in opioid prescription rates that correlated with an increase in opioid exposure to the population over the same period (2004 to 2010) and this increase also paralleled an increase in adverse events such as drug-related fatalities (Porucznik et al., 2014). Regrettably, the authors stated that more research was needed to determine the *user-related risk factors* on which effective intervention can be based and did not include the *provider-related risk factors* involved in streamlining the related prescription rate.

The link between prescription opioids, though not straightforward, has been verified by various published articles. One such study conducted by the NSDUH revealed

that 22.6 million Americans (8.9%) were illicit drug users in 2010 (Manchikanti et al., 2012). During that same period, 7 million were abusing marijuana, 5.1 million were abusing pain relievers (Manchikanti et al., 2012). Of those that were abusing pain relievers, 17.3% originally obtained the opioid from a prescription (Manchikanti et al., 2012). The following year, 2011, 238 million prescriptions for analgesics were written and 136.7 million (over 57%) were for the opioid hydrocodone (Manchikanti et al., 2012). Sadly, 60% of the opioid related deaths were from standard prescriptions, and most were for morphine of over 100 mg per day, the other 40% of the deaths were from opioid received illegally, from “multiple prescription, doctor shopping and drug diversion” (Manchikanti et al., 2012).

Four years later a cross-sectional study was conducted to assess the association between prescription opioid and opioid abuse. This determined that over 37% of the U.S. population had used prescription opioids that previous year, with some 11.5 million reported misusing the drug, and almost 2 million developing an opioid use disorder (Han et al., 2017). The study also revealed that most of those who abused the drug were uninsured, underemployed, had a low income, and a history of mental health issues (Han et al., 2017). The most important insight from this study was the fact that among those who misused opioids, 59.9% did not have a prescription for the drug at the time and obtained it free from friend or relative who did (Han et al., 2017). Similar evidence implicates the deviant opioid prescription patterns that must be addressed, as they can make opioids available for misuse and abuse and contribute to the opioid epidemic.

Addressing the trend in opioid prescription and zeroing in on the prescription in the ED, a study using research consortium data was conducted in 2014. The researchers wanted to compare the data with the previous survey extrapolation findings and used a national sample of ED patients that included 1.4 million visits across 19 EDs over a one-week period (Hoppe et al., 2015). Of the 1.4 million, 27,516 were evaluated, and 17% (3,284) of those were discharged with an OPR prescription (Hoppe et al., 2015). The most common conditions were back pain (10.2%) and abdominal pain (10.1%), most frequent OPR being oxycodone (52.3%), more than 99% of which for the immediate release form (Hoppe et al., 2015). The results reinforced the previous findings and confirmed the upward trend in prescription rate even after national prescription guidelines were disseminated.

Race/Ethnicity and opioid prescription rate. Identifying the risk factors involved in opioid prescription rate is critical to responding to this crisis. In the emergency setting it is difficult to assess patient's potential for drug abuse and ED providers are required to make quick decisions without compromising patient care. Studies have indicated that sometimes these decisions are based on the providers' subjectivity and certain factors play a role. Among the many factors, a patient's race-ethnicity, as with other areas of medical care, is foremost in the disparity that exists in receiving opioid therapy (Joynt et al., 2013; Knopf, 2017; Tamayo-Sarver et al., 2003). One study found significant racial-ethnic differences and they may reflect unconscious provider biases, with providers being less conservative in their opioid prescribing with non-Hispanic Whites than with non-Hispanic Blacks (Singhal et al., 2016). As far as the

findings were concerned, when it comes to prescription opioids, race matters.

In a nationwide study that looked at pain management in the ED confirmed the racial-ethnic disparity. The study restricted the patient diagnosis to nontraumatic acute abdominal pain according to a uniform ICD-9 definition and included all adults in the 2006-2010 NHAMCS database (Shah et al., 2015). A risk-adjusted stratified analysis of the modulators including, ED wait time, number of diagnostic tests, and subsequent admission, was conducted to determine the relationship between race and analgesic in the ED. The study found that Blacks and other minorities had a 22-30% lower odd of receiving analgesics compared to whites and the difference in odds was greater for 18 to 21 age groups (Shah et al., 2015). Interestingly, not only were more Whites being prescribed opioids, they dying by greater numbers from opioid overdose.

Race plays a major role in the discrepancies in the unfolding of the response to the opioid crisis. The decline in the life expectancy of Whites started a few years after the FDA approved OxyContin (1998) and TJC made pain the fifth vital sign (2000) and opioid-related mortality among Whites was found to be three times that of blacks by 2003 (Case, Deaton, Cutler, Skinner, & Weir, 2015). As the drug overdose dilemma caused the life expectancy of U.S. Whites to decline, research confirmed the connection to the disparity in marketing and access to the drugs. Opioid manufacturing and dispensing was controlled in such a way that was more likely to be to White patients than non-Whites (National Academies of Sciences, Engineering, and Medicine, 2017). Furthermore, laws were put in place that distinguished crack cocaine from its powder form and differentiated the abuse of prescription opioids addiction from that of the heroin addiction

(Case et al., 2015). When news of the mostly middle-class, white-color opioid dependents surfaced, the prescription programs and the naloxone and buprenorphine clinics were the response versus the high rate of arrests for illegal heroin use (Case et al., 2015).

According to Cheung (2014), environmental exposure was the number one risk factor for potential abuse, emphasizing the need for careful monitoring of the prescribing practices surrounding opioid medication. But even as more information of this type was became available, the rates of abuse continued to increase and the racial disparity among those affected persisted. Figure 5 includes age-adjusted opioid analgesic poisoning rates, by race and ethnicity.

Figure 5. Age-adjusted opioid-analgesic poisoning death rates, by race and ethnicity: United States, 1999–2011

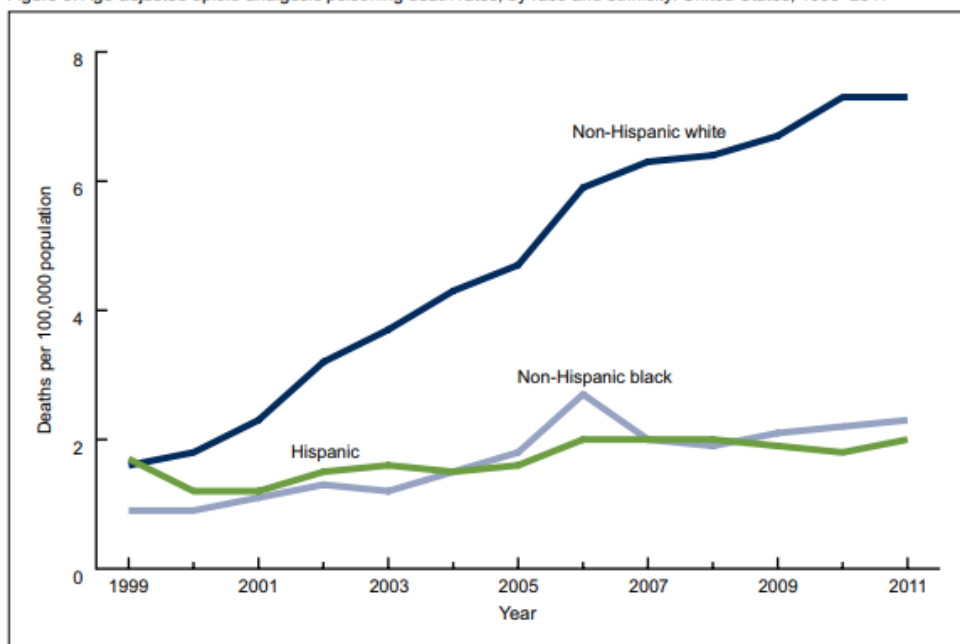


Figure 5. Age-adjusted opioid analgesic poisoning rates, by race and ethnicity (CDC, 2011).

Socioeconomics and opioid prescription rate. Patients in a lower socioeconomic (SES) have a have a greater risk for many medical issues. These patients are less like to receive proper health care, due in part to limited access to primary care, low employment and relatedly inconsistent insurance (Hudley et al., 2014). SES is another one of the factors contributing in the disparity of that exists in administration of pain treatment. A qualitative, one-on-one interview study indicated that providers' perceptions of patient's SES and attitudes towards those in a lower SES affects their treatment of their chronic pain patients (Hollingshead, 2016). These pain management decisions were influenced by the health insurance and other signs of financial constraints (Hollingshead, 2016). The prescribers expressed suspicion towards these patients as drug-seekers and believed that being in a lower SES puts patients at greater risk of opioid abuse (Hollingshead, 2016). A comprehensive study using PubMed, CINAHL and PsycArticles databases conducted a similar study and confirmed biases against those in lower SES, which limited their access to opioids and other analgesics (Maly & Vallerand, 2018). These biases, not unique to pain treatment, can result in unrelieved pain and unnecessary physical, mental and emotional suffering for those in the minority communities.

Despite the significant role that SES plays in the opioid epidemic, studying it is challenged because most data resources do not contain direct measures of this factor. Two of the more popular studies on relationship between SES and opioid prescription rate were forced to use nSES (neighborhood socioeconomic) instead of SES. nSES is determined based on the measures of average income, education and poverty level for the

patient's zip code of origin (Gebauer, Salas, & Scherrer, 2017). The national study, using NHAMCS data from 2006 to 2012, conducted a logistic regression and determined that patient's in the highest nSES bracket had greater odds of being prescribed opioids, even with the same level of pain (Joynt et al., 2013). The results also indicated that Blacks and Hispanics were less likely to be prescribed opioids, regardless of the SES bracket (Joynt et al., 2013). A more recent study, using Primary Care Patient Data, contradicted the previous study, as lower nSES correlated with greater odds of being prescribed opioids (Gebauer et al., 2017). The researchers noted however, that this study restricted the patients with to those with a 'new' diagnosis of back pain and that the findings indicate the providers were non-compliant with the treatment guidelines for the new back pain condition (Gebauer et al., 2017).

Prescription rate variation among ED providers. The research and anecdotal evidence point to a connection between the increase in the rates of prescription opioids and the increase in opioid-related injuries and deaths. The previous two decades has seen a significant increase in the number of deaths from drug poisoning, and more specifically rate for deaths by opiates have quadrupled (Pomerleau et al., 2016). These deaths are not occurring in a vacuum as there is a concurrent increase in prescription rates across the country. In 2008 there were 205 million prescriptions for opioids, but in 2012 almost 259 million OA prescriptions were filled, and even more were written (McDonald, Carlson, & Izrael, 2012)(Pomerleau et al., 2016); Pomerleau, 2016). Specific to the ED, in 2008, 20.8% of all patients visiting the ED were prescribed an opioid, but in 2010 it rose to 31%, and 144,600 visits for non-medical use of opioids in 2004, would grow to 305,900

fours later (Center for Disease Control & Prevention, 2010). Opioid prescription, including those in the ED, and opioid abuse and opioid-related deaths are to be correlated.

For providers in the ED, as with others who are involved in pain management, treating pain means balancing the comfort of the patients with the risk of overdose and addiction. Since over 42% of the ED visits are related to pain symptom (Centers for Disease Control and Prevention, 2012), deciding whether to prescribe opioid and at what dosage of the prescription is common decision for ED providers. These decisions are complicated by the need to prioritize patient satisfaction and admonitions to beware of potential abusers. The current prescription guidelines, though intended to help, are not based on evidence but on the consensus of experts and are therefore not reliable (AMCP Partnership Forum, 2015). Unfortunately, ED provider has received inadequate training in balancing these many, nor does the ED setting afforded them the time or resources to administer (Committee on Advancing Pain Research, Care, 2011). These shortcomings cause each provider to make their own individual choices and as a result disparate prescribing decision produce wide variation in prescribing patterns.

The report of the variation in ED prescription rates among providers was not novel. Over a decade ago (Tamayo-Sarver, Dawson, Cydulka, Wigton, & Baker, 2004) published finding that reflected the rising trend in opioid prescribing among ED physicians. They reported that for patients requesting something strong for their pain, 10% of the physicians responded positively, 10% responded negatively, while mostly the physician's decisions varied significantly when faced with identical clinical scenarios

(Tamayo-Sarver et al., 2004). But it would be almost a decade before the topic would receive attention when physician and epidemiologists, Dr. Mazer-Amirshahi, would conduct two studies on the subject. The first one reported on general opioid prescribing in the ED (Mazer-Amirshahi et al., 2014), and another two years later, on the opioid prescribing habits of attending physicians (Mazer-Amirshahi et al., 2016), and both studies would reflect a troubling upward trend but that the rise was not uniform among the different types of providers in the ED.

Other researchers have explored the concept of ED provider opioid prescription rate variation. A study conducted in 2014 in two tertiary care military hospitals looked at the prescribing practices among the various types of ED providers. Variables included the list of opioids, the diagnosis of chronic pain both based on the International Classification of Disease (ICD-9) codes, the provider type, provider gender, number of pills for each prescription, the type of opioid and opioid refills if any (Ganem et al., 2014). After applying these selection criteria on data for the last three years, 1,322 (out of 28,165 total visits) patients qualified with a diagnosis of chronic pain, (Ganem et al., 2014). Opioids were prescribed to 443 (34%) of the chronic pain patients, by 103 opioid providers, 79% of whom were physicians and 19% were physician assistants (Ganem et al., 2014). The results indicated that the physicians were more likely to prescribe opioids than the physician assistants (Pas) (77% versus 45%) and the civilian doctors were also more likely to prescribe opioids than the military doctors (58% vs 42%) (Ganem et al., 2014). These results indicate that military doctors and PAs were more selective in their opioid

prescribing, and this may reflect differences in training for each group relative to the others.

So now that the variation rates were confirmed among the ED providers, what factors cause these variations? A 2016 pilot study aimed at identifying some of the factors influencing providers' prescribing decisions was conducted among 203 ED providers (Pomerleau et al., 2016). Though limited to one hospital, the study was a first of its kind, with a variety of different types of providers. The participants included attending physicians, residents, nurse practitioners and physician assistants, and the data collection survey was a self-rating of the factors influencing their opioid prescribing decisions. The researchers discovered that a patient's opioid prescription history and their history of substance abuse or dependence were the factors that had the greatest influence on the provider's prescribing decision (Pomerleau et al., 2016). Factors such as patient's diagnosis and level of distress were secondary, indicating that ED providers were giving strong consideration of the link between the opioid prescription and the ill effects of the drug. But despite these considerations there was significant variation in prescription rates among these providers.

The same 2016 pilot study indicated that differences in provider training was one of main factors influencing prescribing decisions. The attending physicians were found to be less concerned about patient satisfaction or the prescribing culture, while the residents placed less importance on the patient's pain intensity or history of opioid use (Pomerleau et al., 2016). The advanced practice providers (physician assistant and nurse practitioners) did place higher importance on the pain intensity, patient satisfaction as

well as history of opioid use (Pomerleau et al., 2016). This was in keeping with the idea that the advanced practice providers tend to spend more time with patients and therefore make better patient evaluation and provide superior patient care instructions. The physicians that were least experienced, i.e. the residents, were more likely to give credence to the requests of the patients and to be more careful to abide with the prescribing culture at the present institution (Pomerleau et al., 2016). It is possible that these decisions are unique to the hospital, but it points to the need for additional training for physician regarding the opioid prescription and pain management in the ED setting and more research in this area provider prescription decision making

One of the most prolific researchers on the subject of opioid prescription rate, Dr. Hoppes has published several of findings. One such research was a retrospective, descriptive analysis that looked at opioid analgesic prescription variation for patients presenting to the ED over a seven-month period at an urban academic hospital. The participants were restricted by a diagnosis of lower acute back pain (LABP) and an opioid analgesic on discharge (Hoppe et al., 2017). There were 23 ED providers, with an average of 25 LABP patients each, resulting in 943 patients in this homogenous cohort (Hoppe et al., 2017). The study found an alarming 22-fold variation in prescribing proportions, which turned out to be 6-fold (12% to 78%) after adjusting for certain patient and clinical characteristics (Hoppe et al., 2017). This significant variation among ED providers, all at the same hospital, for a homogenous cohort, point a serious situation. Given that prescribing practices are linked to opioid abuse and the opioid epidemic, this

imply that more needs to be done as far as refining the guidelines, improving adherence to the guidelines and educating providers.

Opioid abuse following emergency department exposure. Given the variation in rate among ED providers, what is risk of addition once having received an opioid prescription from one of these providers? A descriptive analysis was conducted to answer this question. The researcher assessed the effect of opioid-prescribing patterns among ED providers and the risk of future abuse, for Medicare beneficiaries visiting the ED during the period 2008 to 2011 (Barnett et al., 2017). This retrospective study looked at the risk of long-term opioid use after receiving an opioid prescription in the ED. They evaluated opioid use for a year after the patient's ED visits for those who had no record of opioid use during the six months prior to their visit. The study divided the ED physicians into quartiles, based on their opioid prescribing rates at their respective hospitals, based on the dosage of opioids they prescribe. According to the findings, while the diagnosis was similar among the two groups, 215,678 received opioid prescriptions from low-intensity prescribers and 161,951 from the high-intensity prescribers but there was 3.3-fold (7.3% to 21.1%) variation in prescribing habits between the low-intensity and the high-intensity ED providers and a *significantly greater risk of long-term use among patients in the high-intensity group* (Barnett et al., 2017).

Another study sought to assess the risk of recurrent opioid abuse following an initiation of use from an ED prescription. This descriptive retrospective study in an urban academic institution Colorado evaluated all the opioid naïve (no previous opioid prescription in the last year) patients diagnosed with an acute pain condition who were

subsequently discharged from the ED over a period of five months. From a total of 5,597 patients records in drug monitoring program database, and 4,801 were selected for analysis and little more than half (2,499 or 52%) were opioid naïve of the 1,420 (57%) did not receive an opioid prescription in the ED 146 (10%) had recurrent use (Hoppe et al., 2014). Of 1,079 who received an opioid prescription, 305 did not fill the prescription and there was an 8% (23) recurrent use for them, and of the 775 who filled their prescription had a 17% recurrent use (Hoppe et al., 2014). These results indicate that receiving and filling an ED opioid prescription, for opioid naïve patients almost doubles the risk of recurrent use in the future.

Yet another study attempted to describe the risk of opioid abuse and iatrogenic addiction after initially exposure to opioids in the ED setting. A cross-sectional survey study conducted on the ED patients presenting with heroin overdose or non-medical opioid abuse symptoms at an urban academic teaching hospital. Of the 122 patients approached, 59 subjects volunteered and completed the survey, and 35 (59%) of which were revealed to have received their first opioid prescription legitimately, 10 (29%) of the 35 obtained them from the ED (Butler et al., 2016). Results indicated that it took six months from exposure to the onset of non-medical use of opioid for 31 of the 35 (88.6%), with 11 doing so in 2 (31.4%), 9 of whom had a history of substance or alcohol abuse prior to their opioid exposure (Butler et al., 2016). The researchers concluded that prescribing short-term opioid does not necessarily result in addiction, but it does play a role in eventual abuse for a significant number of patients and more research, with a greater number of patients, is needed to address this issue.

In a most recent study that looked at the possible link between ED opioid prescription and the potential for long-term use in opioid-naïve patients. Unlike the studies discussed previously, this one compared the risk of ED prescription with risk of a prescriptions received in settings other than the ED. The researchers used the data from the administrative claims made by Medicare Advantage (elderly and disabled) subscribers compared it with other commercial insurance and the analyzed the rate of developed long term use, agreement with CDC guidelines, and the time from initial prescription to long-term opioid use for both groups (Jeffery et al., 2018). The claims data for the period 2009 to 2015, found that of the 5.2 million opioid prescription filled, that 13.4% (twice as likely) of disabled beneficiaries were more likely to progress to long-term use compared with the 6.2% of the elderly, and only 1.8% for the commercially insured (Jeffery et al., 2018). Interestingly, the ED prescriptions were more compliant with the CDC guidelines than non-ED prescriptions with respect to lower dosage, immediate-release formulation and shorter number of days (Jeffery et al., 2018). Additionally, the commercially insured (46%) were least likely to progress to long-term use, compare with the aged (56%) and the disabled (58%) Medicare beneficiaries (Jeffery et al., 2018). The authors noted caution about the ED apparent compliance and the correlation with lower risk as this study was the limited by several factors including: short time measure for determining long-term use; only 2% of the dosage was for long-acting, extend release form; and a previous history of substance abuse was not considered (Jeffery et al., 2018).

The outcome of opioid prescription guidelines. Prescription medications are the primary cause of injury death, with most of the drugs involved being opioid analgesics, and the lack of any increase in pain complaints is contrasted with a significant increase in opioid prescriptions dispensed in the ED (Mazer-Amirshahi et al., 2016). The persistence of this trend and the established link between long-term opioid therapy and physiological dependence and addiction made addressing this issue a priority. The ACEP chapters of Washington and Oregon states (and eventually New York) were the first to create prescribing guidelines that essentially advised against prescribing long-acting opioids, limiting prescriptions to a three-day supply, and desisting from replacing lost prescriptions (Poon, 2014). But the example set by these three states were not readily embraced by other states, who either chose no prescribing guidelines or use some other strategy.

Other EDs tried to address the problem by implementing prescription drug monitoring programs (PDMPs), an internet based database for recording and looking up patient's prescription drug history, established in 2008 (Hoppe et al., 2015). But the few studies conducted to investigate the effect of PDMPs on provider prescribing behavior have shown not so positive results. One state wide study in Ohio found that use of PDMPs resulted in a 40% change in prescribing behavior, and 66% the providers who changed decreasing their rate, while 40% increased theirs (Baehren et al., 2010). A smaller study of 38 ED providers found that the change in prescribing behavior following PDMP implementation was minimal (9.5%) most of which was an increase in opioid prescriptions (Weiner et al., 2013). Yet another study among attending and resident

physicians found an overall decrease in prescription, but incidentally, 38% of the attending increased their prescription after exposure to the PDMPs, while not resident did (Feldman, Skeel Williams, Knox, & Coates, 2012). A national survey medical toxicologist revealed that most had either not heard of the PDMPs and those who did found them too difficult to access and use (Perrone, DeRoos, & Nelson, 2012). These state-wide PDMP may have potential to help ED providers reduce the risk of opioid abuse in some patients, the tool needs more work and its adoption and use needs to be universal before the real benefits are experienced.

The concern for the opioid-related deaths have resulted in the several agencies instituting their own guidelines governing the prescription of opioids. On a national level, the FDA amended their risk evaluation and mitigation strategy (REMS) program for including in the physician education curriculum information concerning the administration of long-acting and extended-release opioids (Sheldon, 2011). On the state level Utah, Washington, and New York, developed their own respective opioid prescribing guidelines to specifically address the EDs to reduce the inappropriate use while still meeting the need of patients for effective analgesia (Neven, Sabel, Howell, & Carlisle, 2012). The Washington state Medicaid also instituted a policy that would deny payment for unnecessary visits ED, forcing ED providers to adopt “best practices” guidelines (Neven et al., 2012). The American College of Emergency Physicians (ACEP) and the CDC have provided clinical policy related to prescribing opioids in the ED. The Oregon chapter of the ACEP published guidelines advising for consistency and against replacement prescriptions opioids in the ED, (Notenboom, 2017).

Clinical policies produced by the ACEP together with the FDA and the CDC sought to address several issues related to the administration of opioid to patients in the ED for who opioid would be the “appropriate treatment modality” (Cantrill et al., 2012). As studies have demonstrated, that although the PDMP was designed for improvement but due to the many limitations, garnered only partial success. The absence of high - quality research concerning the effectiveness of opioids long-term and or relative to other treatment options leads physicians to rely on their own judgement and experience. ED patients invariably include opioid abusers, yet no randomized controlled trial (RCT) or prospective observational cohorts are conducted to understand this demographic. Also, comparison the effectiveness and eventually standardization of the metrics used in the different PDMP across the different states is critical. Studies examining the use the different opioid types (hydrocodone, oxycodone and fentanyl) compared with non-opioid therapies and the historical factors of the ED patients. Finally, understanding the post-discharge behavior of opioid prescribed patients relative to the follow-up provisions stratified by pain complaint, diagnosis as it relates to results and opioid diversion.

The NYC ED discharge guidelines for opioid prescribing consisted of a set of nine directives or advice modules (Chu, 2013). The note states that the guidelines should not replace clinical judgement and they should not replace appropriate patient care as determined by the physician. In summary, providers are admonished to consider short-acting opioid, starting with the lowest dose and short course. The patient should be assessed for current opioid use and abuse history, use non-opioid analgesics for recurrent pain. According to these guidelines, the long-acting drugs are sustained-release

oxycodone, methadone, sustained-release morphine, fentanyl, and the extend-release form of oxymorphone, and hydromorphone. The short-acting drugs are codeine, immediate-release oxycodone, Vicodin, immediate-release morphine, hydromorphone, and immediate-release oxymorphone.

Despite treatment guidelines, which are no more than suggestions since they lack backing of any research evidence of benefit or long-term outcomes, there are significant variations in prescription pattern (National Academies of Sciences, Engineering, and Medicine, 2017). In fact, the limited evidence that exists points to significant harm and addictions, which is supported by the present opioid epidemic. In many cases, the descriptive studies indicate that despite efforts at intervention, treatment guidelines and use of prescription drug monitoring programs (PDMP), there is very little consensus even when the patients present with identical scenarios (Hoppe, 2017). These ED providers are on the frontline in dealing with the issue of pain management in the field and doing their best to provide quality healthcare. This has motivated ongoing research to understand this variation among ED providers in the hopes of minimizing it.

Summary and Conclusions

Pain is a universal experience and the oldest medical problem, and the history of medicine and public health is rich with tales of the efforts to respond to and deal with this condition. Treating pain has evolved over the centuries from incantations, gases and potions to pills and injections, and technological advancement made pain treatment more and more effective. One of the themes that runs through the story of pain management is the use of the opium in various form as well as the accompanying problem of abuse and

addiction. But opioids, in its many forms remains one of the most powerful options for dealing with chronic, severe pain and this is evidence by its widespread use in the practice of medicine. The widespread use of opioids, both legally and illegally, has resulted in the opioid epidemic, which is now a major public health crisis.

As the most common condition for which patients turn to medical treatment in the ED, ED physicians in the ED are at the frontline of the struggle to pain management administration. They are faced with the challenge of relieving patients' pain while at the same time mitigating their risk of opioid misuse, abuse and addiction. While much of the focus of the response to the opioid epidemic have been on patient's characteristics, evidence exists that provider biases also play a role. The prescribing decisions of ED providers are consciously and unconsciously affected by their perceptions of their patients as well as their own traits and experiences. Limited research has indicated differences in prescribing behavior among ED providers that results in pattern variation, but more needs to be understood about this. Despite the prescribing guidelines and the prescribing monitoring programs, these patterns persist, indicating the need to more research into the drivers behind these prescribing patterns so that they can guide the development of effective intervention strategies.

Chapter 3: Research Method

Introduction

The objective of this research was to determine the role of ED provider type on the rate of opioid prescription occurring in the ED. In this chapter, I describe the subjects and the methodology employed to address the research questions. The analysis was performed on secondary data (the NHAMCS), which were collected by the NHCS. The surveys conducted by the NHCS are designed to provide health care statistics to those who conduct research on various topics involving health care organizations and the services they provide to the U.S. population. The NHAMCS contains information on opioid prescriptions by ED providers to patients visiting the ED, which made it ideal for answering the research questions.

The chapter is divided into three main sections culminating in an overview of the data analysis procedure. The first section includes the characteristics of the sample participants or subjects, information on how they were selected, and a description of how missing data or attrition was treated. The second section includes information on the instruments used to collect the data, the data collection procedure, and the various measures and constructs that are included in the data set. This section also includes a discussion of the external and internal validity associated with the research methodology. In the final section of the chapter, I present a detailed description of the data analysis plan, complete with a discussion of each of the research questions, the related statistical tests, the rationale for choosing the test, and the means by which results were evaluated for statistical significance.

Research Participants

The NHAMCS of the NHCS

The National Hospital Ambulatory Care Survey (NHAMCS) and the National Ambulatory Medical Care Survey (NAMCS) are the two survey instruments devised by the National Center for Health Statistics (NCHS), a branch of the Centers for Disease Control and Prevention (CDC), used to collect information about health care utilization across the various medical institutions around the United States. The ambulatory medical care provided in physicians' offices all over the United States is the principal means by which the majority of Americans access health care (Hsiao, 2010). Beginning in 1973, the NAMCS was used to collect and publish relevant information on these visits (Hsiao, 2010). Almost 20 years later (1991), NCHS created the NHAMCS to broaden the scope of the collected data to include community health centers, hospital EDs, outpatient departments, and all types of ambulatory surgery locations (NCHS, 2015a). The objective was to gather information about the health care provided by hospital emergency and outpatient departments across the United States and to make it available to the public (NCHS, 2015a).

Adding the NHAMCS to the NHCS activity was important because visits to hospital emergency and outpatient departments (OPD) make up the second largest (after ambulatory care provided through physician's offices) segment of medical care in the United States and comprise a different patient demographic (CDC/NCHS, 2017). At the start, there were 1.43 billion ambulatory visits, 164 million of which were to EDs and OPDs, annually (McCaig & McLemore, 1994). Collecting the relevant data became

increasingly necessary as the population aged rapidly and there was an increasing number of patients without health insurance, along with a growing array of medical modalities. There was a growing sense that it was important to understand the impact of these societal changes on the organizations involved and on the delivery and cost of ambulatory care in the United States. In response, the NHCS convened a panel of experts from the National Academy of Sciences and the Institute of Medicine and outlined the design for a survey that would reach out to those involved in hospital ambulatory medical care (McCaig & McLemore, 1994). Together with the NAMCS, the NHAMCS has become an invaluable tracking instrument, collecting important health care utilization data from across the country and making it publicly available to those who wish to use it.

Both the NAMCS and the NHAMCS survey instruments have been revised and updated several times since they were first introduced. Additional questions were added to both in 2003 to reflect changes to electronic health record systems, while in 2006, a new stratum of community health centers was added to the NAMCS (CDC/NCHS, 2017). Another change was the assignment of unique drug codes for all pharmaceuticals based on the Multum's Lexicon Drug Database, where each drug containing multiple ingredients was given a single code to replace the generic drug code for each ingredient (CDC/NCHS, 2017). Additionally, in 2010, makers of both surveys began collecting laboratory tests results, and a year later the five-fold increase in sample size for the NAMCS allowed for state-based estimates of health care utilization (NCHS, 2015b). Finally, beginning in 2012, the clinical data on cardiovascular diseases and stroke were

monitored by a heart disease module that was added to both survey instruments (NCHS, 2015b).

Sample Selection for the NHAMCS

The intent of the NHAMCS was to gather information about the ambulatory care provided in hospital emergency and outpatient departments, and it includes both free-standing and hospital-based institutions (NCHS, 2015b). Although both OPD and ED data are collected, the public files contain only data from the ED surveys. Ambulatory care is the way most Americans receive medical care, and the NHCS, recognizing that differences in demographics and other characteristics might affect ambulatory care visits, instituted the NHAMCS to gain a more complete picture of the national patient profile. The data file published by the NHAMCS contains an account of each patient visit, including the medical record pertaining to each visit, the characteristics of the ED personnel providing the care, and the facility for each institution in which the ED is located (NCHS, 2015b). Not all the variables collected in the survey are included in the published form, but they can be formally requested from the NHCS.

The NHAMCS is designed to be a national representation of patient visits made to hospital EDs, outpatient surgeries, and outpatient clinics, excluding federal, military, and Veteran Administration hospitals, in all 50 states and the District of Columbia (CDC, 2017). The sampling was based on geographic location, specifically counties, and the various emergency service clinics in the hospitals found in each location. Data for the NHAMCS are collected from the patients' medical records and include notes on their demographics (age, gender, race / ethnicity), their symptoms and reason for visit, the

diagnostic and screening services provided, the types of health professional seen, the diagnosis received, and the medications prescribed (Hsiao, 2010; McCaig & McLemore, 1994). One of the advantages of the NHAMCS over similar research data collected is the inclusion of institutions other than academic medical centers (Kea, Fu, Lowe, & Sun, 2016a). Inclusion of these data helps the NHAMCS provide a more well-rounded view of health care services and the patient body receiving care in the ED and OPD. This also makes the findings based on its analysis more generalizable.

Sampling Process for the NHAMCS

The NHAMCS was designed to collect a probability sample of visits to the ED to generate a national estimate, using a four-stage sampling design (National Center for Health Statistics, 2015b). The process starts with sampling across the entire U.S., then from specific regions in the U.S., followed by the emergency departments located in those regions, and finally from the various types of institution-ownership for each of the EDs. The outlined sample selection included the following four steps:

1. Sampling counties or metropolitan area from the 50 states and D.C., selecting 112 primary sampling units (PSUs) from among 1,900.
2. Selecting from each of the PSUs, hospitals meeting certain eligibility characteristics and also providing ED services
3. Choosing different ownership types from the eligible hospital with ED, excluding all Federal and institutionalized hospitals and assigning those with less than six in-patient beds to a separate stratum.

4. Finally, selecting a designated number of patient records, from all ED visits, for eventual inclusion in the data set.

The first-stage of the sampling process was based on geographic location and generated 112 PSUs. This came from a subsample the total of 1990 PSUs, based on counties, groups of counties, county equivalents, towns, townships, minor civil divisions, or metropolitan statistical areas (National Center for Health Statistics, 2015b). The original numbers were according to the 1980 Census of Population (1985-1994 NHIS) projection, and were stratified based on socioeconomic, demographics, and population size (National Center for Health Statistics, 2015b). Those selected for the NHAMCS included 26 of the largest PSUs, 26 of the second largest PSUs and then one from each of the remaining strata of the PSU population (National Center for Health Statistics, 2015b).

Selecting hospitals from the 112 PSU involved finding ones that were in the 1991 SMG Hospital Market Database and had an average stay of less than 30 days per patient, as well as a general (medical or surgical) or children specialty and not deemed Federal, institutional or military hospital (National Center for Health Statistics, 2015b). Of the 6,249 eligible hospitals, 5,582 (89%) had EDs and 5,654 (90%) had OPDs, and were classified into four categories (ED only, OPD only, ED and OPD, and no ED or OPD) (National Center for Health Statistics, 2015b). Further stratification was based on hospital size, on volume of visits, type of ownership (non-profit, for-profit), and region (National Center for Health Statistics, 2015b). Included EDs were selected from each of the necessary stratum and assigned for data collection.

Of the various PSU categories, systematic random sampling yielded 550 hospitals, with an ED and/or OPD, which were divided in groups of 30-35, with every group assigned to a 4-week reporting period (National Center for Health Statistics, 2015b). Based on the selection criteria, 377 of the 457 hospitals qualified as having 24-hour emergency services, but only 267 agreed to participate in the survey, resulting in a 70.8% sampling response (National Center for Health Statistics, 2015b). Of the 267 participating hospitals, 83% complied with the minimum requirement of providing the forms for at least half of their expected sample visits, yielding a total of 21,061 completed electronic Patient Record (PRF) forms, resulting in an initial response rate of 77.8%, and an overall sample response rate was 55.1% ($77.8 \times 70.8\%$) (National Center for Health Statistics, 2015b).

Method of Data Collection

Field Representatives and Confidentiality

The data collection was conducted by staff from the U. S. Census Bureau, which selected and trained the Field Representatives (FRs) and monitored the data collection process. There was a 6-week obligatory induction phase, prior to the 4-week reporting period, during which the ED staff were trained with the permission of the hospital administration (National Center for Health Statistics, 2015a). During induction, the assigned FRs worked with the ED department staff to verify eligibility, and to obtain necessary IRB approval. This induction also involved sending out correspondence, contacting the administrators, collect relevant data about the institution, and developing appropriate sampling plans. Once inducted, the ED staff was trained in the correct data

collection procedure and the proper use of the Patient Record forms (PRFs). Since the 2015 NHAMCS data is based on computer-assisted tool, that replaced the paper-based ED record forms in 2012, all of all ED records are now completed by the FRs (National Center for Health Statistics, 2015b). The hospital staff collected daily listings of all visits during the assigned 4-week reporting period and the FRs selected the visits, based on the predetermined systematic random sampling, to generate at least 100 PRFs per ED clinic.

Under the guidance of the Research and Ethics Review board of the NCHS and the Health Insurance Portability and Accountability Act (HIPAA) the data collection was safeguarded. No personally identifying information (name, address, Social Security number, etc.) was collected by the NHAMCS and in 2013 informed consent and patient authorization requirement waivers were granted allowing the release of medical record by relevant healthcare provider (National Center for Health Statistics, 2015b). The FRs, who were trained in the Privacy Rule on how hospitals can disclose limited health information for research without violating in privacy laws, masked identifying confidential information on the patient or the facilities for values like ‘race’ and ‘diagnosis’, and top coding values such as ‘age’ (National Center for Health Statistics, 2015a). The NHAMCS data is publicly available, but approval from Walden’s Institutional Review Board was obtained prior to conducting research on the data.

Instruments: Survey Material

The automated survey tool (see Appendix A) used for the 2015 NHAMCS data collection, first distributed in 2012, was redesign from the traditional paper-based version to make computer-assisted data collection possible (Center for Disease Control and

Prevention, 2017). The redesign included additional specifications about the survey's appearance, -changes in wording, answer choices, and variable length- as well as the addition of a number of new help-screens and prompt-fields to improve data entry accuracy (National Center for Health Statistics, 2015b). The initial visit of the field representative was for the induction into the use of the hospital induction form (see Appendix B). This determined the list of all ED clinics and service areas at each hospital, and further classification based on expected number of patient visits over a the 4-week period (National Center for Health Statistics, 2015b). Selecting the records to include in the data set required satisfying specific criteria, as visits were to be defined as a direct, personal exchange between patient and provider (physician, staff member acting under physician's direction), for seeking care and rendering health services. The number of Patient Record forms collected were obtained with a random selection of every *n*th visit, based on the expected number of patients and the desired number of 100 for each ED (National Center for Health Statistics, 2015b).

Validity and Variance Estimation

The sampling variability is measured by the relative standard error (RSE), which is expressed as a percentage and is calculated by dividing the standard error of the estimate by the estimate itself. The SUDAAN software was used to produce the standard error as it accommodated the complexity of the sample design, especially for clustered variables such as 'race' and 'source of payment' (Hsiao, 2010). Software packages such as SPSS is useable with the 2015 estimates, if not combined with previous years. It may produce underestimation and a higher likelihood of Type 1 error, and a significant

difference at an alpha of 0.01 level (instead of 0.05) was recommended by the NHCS researchers (National Center for Health Statistics, 2017).

The data processing involved several steps for checking, configuring and transforming the data into the files that are published and the NCHS FRs were charged with reviewing to check for errors. The quality control for the medical and drug coding operations was subject to a two-way, independent verification process and after independently re-keying and recoding a random selection of 10% of all PRFs, the error rate was between 0.3- 0.9% (National Center for Health Statistics, 2015a). All coding variations or illegible entries for cause of injury, medication items, diagnosis, etc. were reviewed and resolved by the NHCS team. According the NCHS the reliability of certain estimates must be based on records that are more than 30 and have a relative standard error of 30% or less, values of which are provided in the appendix for the data summary file. These estimates are produced from the 'patient visit weight', as the file contains an entire sample of 21,061 visits representing an estimated 136,943 visits made across the U. S. (National Center for Health Statistics, 2017).

Research Design and Approach

Secondary Data: NHAMCS Data Set

All the data collection and processing for the NHAMCS was conducted by the U.S. Census Bureau field representatives (FRs). These FRs worked with the hospital staff ensure that the data collected was accurate and reliable. The patient information included demographics, reason for visit, vital signs, cause of injury, diagnostic test, diagnosis, procedure received, medication prescribed, provider consulted, and disposition. This

current research will use only the 2015 NHAMCS data and will include the specific variables- ‘opioid prescription’ as the dependent variable; and ‘provider type’ as the independent variable, and ‘race’ and ‘payment source’ as possible interaction variables, and measures of ‘age’, ‘gender’, ‘pain-scale’, and ‘triage’ as control variables. The reported measures are based on sample data that was weighted to produce unbiased annual national estimates and include standard errors for each estimate. The visit weights take the survey design into consideration and are based on four elements: inflation by reciprocals, adjustment for nonresponse, population ratio adjustments and weight smoothing (Kea et al., 2016a; National Center for Health Statistics, 2015a). The results are subject to both sampling and non-sampling errors, from reporting and processing errors as well as from incomplete or missing responses.

Sample Size Determination

Determining the appropriate size of the sample is required to ensure reliability of detecting the true effect, if it exists, and adequately answering the research questions. Generally, sample size determination involves several simplifying assumptions and the greater the variability in the outcome variable the larger the sample size required (Substance Abuse and Mental Health Services Administration, 2016). For this research the question of determining the effect of ED provider type differences on the probability of opioid prescription, logistic regression analyses conducted. For this type of analysis, there are some basic parameters that should be considered: i) how precise should be the estimations; ii) how reliable are the results; iii) how much variation is acceptable; and iv) how small of an effect size is expected (Substance Abuse and Mental Health Services

Administration, 2016). Fortunately, there are many tools available that allow the use of educated guesses, guided by previous research, to make reliable a priori determination of sample size for this type of statistical analysis.

The G*power analysis tool was used to determine the sample size for this quantitative, statistical analysis. Although there are no specific guidelines available for using this tool for logistic regression, some extrapolation based on its use for other tests have proven useful. Research conducted on the subject of variance in the rates of opioid prescription reported ranges as low as 11% and as high as 40% (Rogers, 2018; Sasson et al., 2018), and odds ratio between 0.5 and 1.3 (Barnett et al., 2017; Pletcher et al., 2008), depending on diagnosis, patient characteristics, hospital type, provider type, etc. (R. M. Dickason et al., 2015; Hoppe et al., 2017; Jeffery et al., 2018; Ringwalt, Roberts, Gugelmann, Cockrell Skinner, & Author, 2015; Weiner et al., 2013). This information was used to make predictions about the variability measures and effect size among ED providers in this data set, and these predicted values were then entered into the G*power software for sample size determination. The specific selections included: **Test family** “z”; the **Statistical test** “*Logistic Regression: Fixed effects, omnibus, one-way*”; as well as the **Type of power analysis** “*A priori: Compute required sample size- given α , power, and effect size*” (Faul, Erdfelder, Lang Albert-Georg, & Buchner, 2007). The following constraints were used to compute the recommended sample size: odds ratio (representing the effect size) = 1.2; X distribution = binomial (for logistic regression), the power = 0.95; and an $\alpha = 0.01$ (for confidence level).

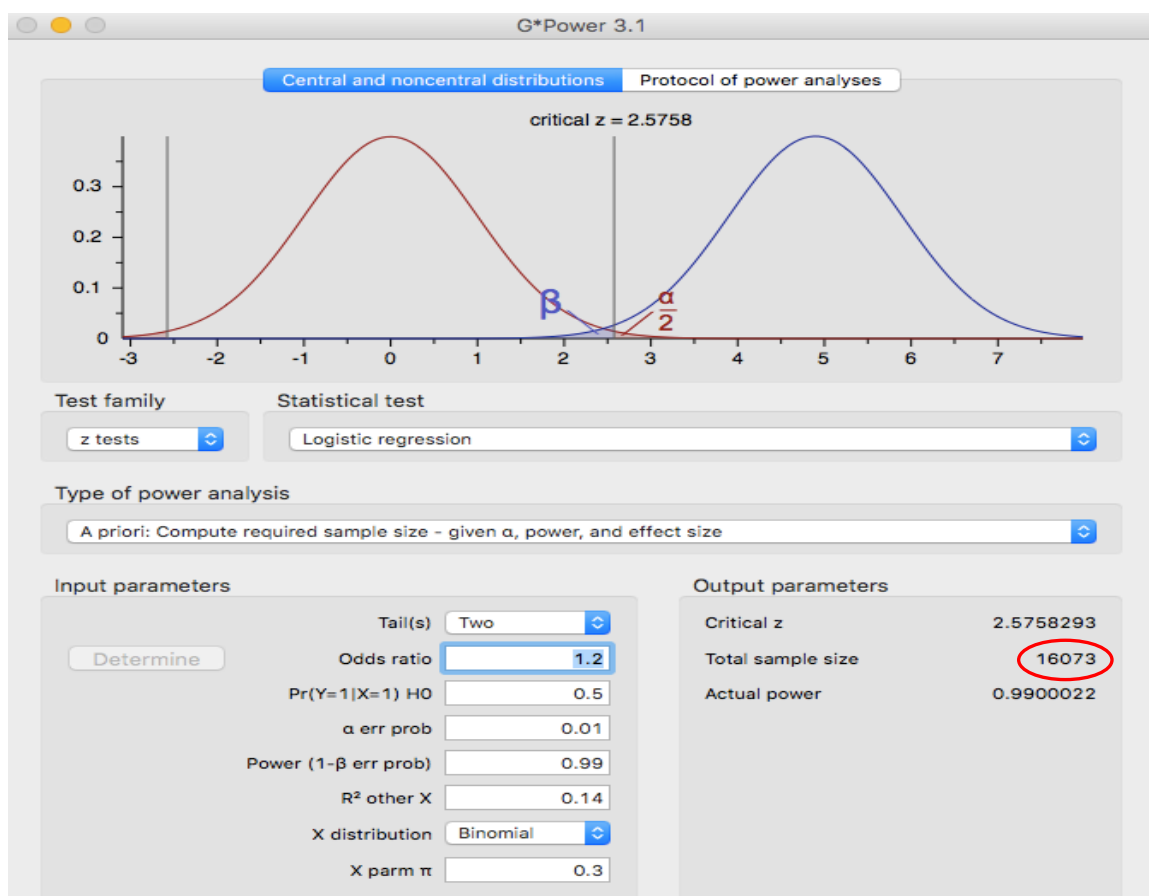


Figure 6 G*Power Sample Size Estimation Output

Power analyses for sample size estimations usually assumes several standard conditions. For linear regressions, these assumptions include normality of the outcome measures, that the error variances among the dependent variables are the same, and that the projected magnitude of the effect size to be detected is correct. For logistic regression, these assumptions are not valid as it is a non-linear model, however a conservative estimation can be determined using reasonable guidelines as have been done in this present study. Using an effect size of 1.2 (odds ratio), which is considered very small for this type of analysis (Ellis & Paul D, 2010), and the NHAMCS recommendation of an alpha of 0.01 (to reduce the chance of a Type 1 error) generates a sample size that is more

than adequate for the detection of differences among the groups being investigated (National Center for Health Statistics, 2015a). The values used generated a sample size of 16,073 and since the data contain more than 21,000 records (representing over 300,000 adjusted visits), it more than meets the necessary power requirement.

Outcome or Dependent Variable: Rate of Opioids

For this study, the outcome variable is the dichotomous response to the question of opioid prescriptions by administered by the ED providers and this new variable was created from the list of prescriptions recorded for each visit. The drug characteristics, assigned using the Multum's Lexicon Drug Database, were coded based on generic as well as their therapeutic components and analgesic prescriptions. The Multum, which is part of the Lexicon Plus database, is a comprehensive database of all prescriptions and some non-prescription drugs on the U.S. market (Cerner Multum, 2018). Analgesics were the most commonly prescribed pharmaceuticals in the ED, amounting to 95,490 (28% of the 340,551) of the reported drug mentions given in the ED or prescribed at discharge (National Center for Health Statistics, 2017). Each drug or each drug-combination is assigned its own unique code, and any mention of an opioid containing 'central nervous system' pharmaceutical was considered an opioid or opioid pain reliever (OPR) prescription. The new variable distinguished OPRs from all other pharmaceuticals, where '0' will represent no OPR prescribed and '1' represented at least one OPR.

Independent Variable: ED Provider Type

The main predictor variable is the 'provider type' of each of the ED provider and reflect their level of training or their medical background. For the purpose of this study,

medical professionals fall into two main categories, those that authorized to write prescriptions and those that are not. In the ED, prescriptions can be written by five categories of ED providers- the attending physician; the resident or intern physician; the consulting physician; the nurse practitioner; and the physician assistant. The various provider types who are included in the main dependent variables are defined in the documentation file as follows:

1. Attending physician: the physician primarily responsible for the patient's care while in the ED and may also be responsible for supervising training interns, residents and medical students.
2. Resident or Intern (first-year) physician: the physician is a recent graduate of medical school and is receiving training in emergency medicine practice.
3. Consulting physician: is the physician called to the ED by a provider to provide consulting care in his or her area or expertise.
4. Nurse Practitioner: an advanced practice registered nurse with qualified clinical competencies beyond that of an RN.
5. Physician assistant: a medical professional who is certified to practice medicine in under the supervision of a physician.

These variables were provided as dichotomous variables each, in the data set and were used as the main independent variables in the logistic regression analysis.

Covariate #1: Race/Ethnicity

The first covariate was that of the race/ethnicity measure for the ED client in each visit. Unlike other aspects of the survey data, with the ‘race’ value record was completed by hospital staff (and not the trained FRs), and despite adjustments, there was still concerns for bias, as 19.4% records for ‘race’ and 24.2% for ‘ethnicity’ were reported as missing or non-response (National Center for Health Statistics, 2017). Fortunately, the weighting of the data that was started in 2005 enables the calculation of department-level estimates. These estimates assume that non-responding facilities had the same characteristics as those responding and therefore the weighted estimates correctly reflect the sample estimates at both the department level and the means of visit characteristics for each variable. This ensures that the variables such as those for race and ethnicity are reliably represented in the data set.

The population estimates in the 2015 NHAMCS ED survey for the different racial groups were based on the 2010 U.S. Census data. The ethnicity variable was used to describe the patient’s national or cultural group with which they identified. In the published data set there is a Race/Ethnicity variable and it contains four categories: Non-Hispanic White, Non-Hispanic Black, Hispanic and Non-Hispanic Other (National Center for Health Statistics, 2017). However, starting in 2009 the NHAMCS resorted to including only three main categories for ‘race’ to eliminate the low-quality race data

(related to other minority races): White and Black, and Other. It is this variable with the three categories what used in the data analysis.

Covariate #2: Source of Payment

The second covariable assessed was that of ‘source of payment’ or how each patient paid for ED service provided, and it is also categorical. This variable was used in place of data pertaining the socioeconomic status, as there was no direct measure of this value. The variable PAYTYPER as recorded in the data set, represents the primary source of payment and was based on the hierarchy of payment options (National Center for Health Statistics, 2015b). The eight options available for responding to the question include:

- 1) Private insurance: paid fully by private insurer (Blue Cross/Blue Shield) or partly (deduction or copay plan) and excluded Medicare Advantage
- 2) Medicare: paid fully by Medicare or in-part (copay, deductible, reimbursement, etc.) and included Medicare sponsored prepaid plan, Medicare Advantage (including Health Maintenance Organizations (HMOs), Preferred Provider Organizations (PPOs), Medicare Medical Savings Account Plans, etc.
- 3) Medicaid or CHIP or other state-based programs: paid in full or in-part by Medicaid plan either directly to the hospital or reimbursed to the patient.
- 4) Workers’ Compensation: charges paid by programs that provide for employees injured on the job qualified to receive financial compensation
- 5) Self-Pay: charges (excluding copays or deductibles) to be paid by patient or patient’s family and will not be reimbursed by third party

6) No Charge/Charity: no fee is charged and includes services provided as charity, special research or teaching purposes.

7) Other: source of payment not covered in any of the above categories and may include organizations such as TRICARE, state and local governments, private charitable organizations and other liability insurance (automobile policy coverage).

8) Unknown: used if the source of payment is unknown or undetermined.

For this research, this variable was regarded as an ordinal variable, with a pseudo ranking based on the hierarchal nature of the categories (as assigned by NHCS). This hierarchal covariate was added as a covariate to the logistic regression analysis and used to determine the effect of 'payment source' on provider type on opioid prescription rate.

NHAMCS Summary Data File Supplied by the NHCS

In the NHAMCS data file, the sampling unit is represented by each patient visit to the ED and a record of patient's visit was defined as a direct, personal exchange between a patient and an ED provider. Only interaction between patients who sought care and received health services were considered official, while visits intended for making payment or dropping of samples, where no medical care was provided, were not. The published summary of the data is based on analysis of the sample visit weight produced from the corresponding sampling fraction at each the sample design stage with respect to time of year, geographic region, hospital ownership (National Center for Health Statistics, 2017). These unbiased estimates provide values of the predictor variables for each of ED visit occurrences, along with percentages, and other important characteristics for comparison and analysis. For each ED visit, a list of all the drugs prescribed are

provided by name and type and is recorded along with several other factors, including patient's race and gender, as well as the associated date, condition, diagnosis, payment type, vitals, discharge or admitted, etc. This study used several of those variables as predictor variables and covariates, based on their relevance to ED prescription variability.

Statistical Research Design

Research Approach: Logistic Regression

Logistic regression is used to analyze data sets containing several predictor variables and a dichotomous outcome. It is a common statistical analysis in medical research because it is able to determine strength of association and to predict risk of disease (or even death) while controlling for several confounding effects (Stoltzfus, 2011). Logistic regression analysis is suitable for longitudinal data, which is collected on the various predictors believed to be associated with an event and these independent or predictor variables can be either categorical, or continuous (Stoltzfus, 2011). In this study, the outcome was the presence or absence of an opioid prescription, the predictor variables included were the ED provider type, and the confounding variables were the race of patient and the type of payment used.

Like linear regression analysis, logistic regression is used to build prediction models, except with the latter, the model is based on probability or likelihood. Logistic regression analysis generates a model with a regression coefficient for each of the predictor variables, the exponential of which represents the odds ratio or the change in the odds of the event relative to a change in the predictor value (Sperandei, 2014). In logistic regression, the categorical nature of the outcome violates the regular assumption

of linearity, but it *is* assumed that there is a linear relationship between the predictor variables and the logit of the outcome variable and so that the strength of the relationship can be correctly estimated (Field, 2014). The other assumptions of logistic regression included the independence of observations, independence of errors (homoscedasticity), absence of multicollinearity, and a sample size large enough such that the least frequent outcome has a minimum of 30 cases for each independent variable (Joglekar, 2015; Lani, 2015; Stoltzfus, 2011).

Assessment the contribution of each predictor was based on the value of its exponential of regression coefficient, the odds ratio, and the respective statistical significance (Field, 2013). A regression coefficient other than zero indicates an effect on the outcome, but a p-value less than α (in this case 0.01) tells whether the effect on predicting the outcome is statistically significant. For determining the statistical significance of the odds ratio, the 95% confidence interval (CI) will also be used, as it represents the range within which the odds ratio value found, 95% of the times this analysis, if conducted on the given data set (Sullivan, n.d.). The precision of the OR value estimated from the position and size of the CI, as a smaller range reflects a more precise measure, and a range that does not cross “1” indicates a genuine effect (Sullivan, n.d.).

Data Analysis

Research Question 1: Provider Type Variation

RQ 1: Is there a significant association between provider type and the rate of opioid prescription in the ED?

H_{01} : There is no significant association between provider type and the rate of opioid prescription in the ED?

H_{a1} : There is significant association between provider type and the rate of opioid prescription in the ED?

A binary logistic regression analysis requires a dichotomous outcome variable, therefore the 'absence or presence' of an opioid prescription was used to create the dependent variable. Although this research involved the analysis of drug data, no separate drug file was generated, avoiding corruption of the estimation of variance. This new variable was generated from the list of drug names (from the Multum's drug code database), recorded for each ED visit, and it was used for all the subsequent analyses in this study. For the first research question, the independent variable was the classifications for the ED provider, already available as dichotomous variables in the data set, was used in the multiple logistic regression (MLR) modelling along with the covariates AGE, PAINSCALE, TRIAGE, and SEX. The odds ratio (OR) generated was used to determine the relative strength the influence of each of the variables on the opioid prescription outcome. The statistical significance, and the rejection of the null hypothesis, was based on the p -value of the z -statistic (Wald statistic) and the confidence interval (CI) of each of the corresponding OR.

Research Question 2: Provider Type and Race

RQ 2: Is the association between provider type and the rate of opioid prescription influenced by the race of the patient?

H_{02} : The association between provider type and the probability of opioid prescription is not dependent by the race of the patient.

H_{a2} : The association between provider type and the probability of opioid prescription is dependent by the race of the patient.

Addressing this research question required the inclusion of an additional independent variable (moderator) and an interaction variable into the logistic regression equation. The dependent and independent variables were the same (Opioid Prescriptions and the Provider Types) as in the first research question, but the RACE variable (the ‘race’ of the patient to whom the medication is prescribed) was added. This analysis also required the creation of an interaction variable (Provider Type x Race) and the generation of two models. The multivariate logistic regression (MLR) was used to estimate the interaction between the independent variables with respect to its effect on the dependent variable. The first model consisted of the DV (Opioid Prescription) and two IVs, (the Provider Type and Patient’s Race); and in the second model the DV was the same, but the interaction variables was added (Provider Type x Race) for each of the Provider Type that was significant in the first. The p -value and CI of each the variables (non-interaction and interaction) was used to determine whether the statistical significance in the models.

Research Question 3: Provider Type and Payment Type

RQ 3: Is the association between prescriber type and the rate of opioid prescription influenced by the patient’s “expected source of payment” variable?

H_{03} : The association between prescriber type and the rate of opioid prescription is not influenced by the patient’s “expected source of payment” variable.

H_{a3} : The association between prescriber type and the rate of opioid prescription is influenced by the patient's "expected source of payment" variable.

Another MLF analysis was conducted to answer third research question. The DV (opioid prescription) and the main IV (Provider Type) remained the same as in the second research question, but the new moderator variable was 'Payment Type'. Like research question 2, two models were generated, with model #1 having the two IVs (Provider Type, and Payment Type) and model #2 having three IVs (Provider Type, Payment Type, and an interaction term, Provider Type x Payment Type). The various statistics used to assess the influence of the new moderator and that of the interaction term on the prediction of the outcome, probability of an OPR prescription. The p -value and the CI of the regression coefficient for the MLR formula in model #2, was evaluated for rejecting or accepting the null hypothesis.

Summary

The purpose of this research project was to examine the role of the provider type on the rate of opioid prescription in the emergency department. The data set was obtained from the National Hospital Ambulatory Care Survey (NHAMCS) data set, which collects information about health care utilization from institutions around the country. The public file of the NHAMCS represents patient visits made to ED and contains extensive surveyed information about the patient and is collected and processed by the NCHS (the National Center for Health Statistics). This data is collected annually and made available a few years later for the all who desire to conduct research on the area of health care

utilization. This study used the 2015 version of NHAMCS, which is the most recently available at this time.

The research questions relate to the role of provider type in predicting the likelihood of an opioid prescription in the ED. The outcome variable was Opioid Prescription (Yes/No) and the independent variable was Provider Type (the attending physician, the resident or intern physician, the consulting physician, the nurse practitioner, and the physician assistant). Logistic regression analyses was used to address the main research question and the additional questions of possible interaction between the covariates (Race and Payment Source) and the main IV (provider type) in predicting the outcome, an OPR prescription.

	Statistical Test	Interpretation	Statistical Significance
RQ1	Univariate Logistic Regression	Exp(B) of IV	p-value, CI
RQ2	Univariate Logistic Regression	Exp(B) of Interaction Term, χ^2 of model 2	p-value, CI $\Delta\chi^2$, p-value
RQ3	Univariate Logistic Regression	Exp(B) of Interaction Term, χ^2 of model 2	p-value, CI $\Delta\chi^2$, p-value

Chapter 4: Results

Introduction

The goal of this study was to investigate the nature of the relationship between ED provider type and the rate of opioid prescription as it occurs in EDs across the United States. In this chapter, I will report on the findings of the statistical analyses performed to address the following three research questions:

RQ 1: Is there an association between provider type and rate of opioid prescription in the ED?

RQ 2: Is the association between provider type and the rate of opioid prescription influenced by the race of the patient?

RQ 3: Is the association between provider type and the rate of opioid prescription influenced by the patient's "expected source of payment"?

To answer the questions, I analyzed data from the CDC's NHAMCS, as it contains information relevant to opioid prescriptions by ED provider type and encompasses the various characteristics of clients using ED facilities. The chapter is divided into four main sections. The first section includes descriptive statistics for the relevant variables (predictors and outcome). In the remaining three sections, I address each of the research questions separately. The latest version of the SPSS software application (SPSS 25) was used to conduct all data analyses.

Descriptive Statistics

Demographic Characteristics

I opened the NHAMCS data set file in SPSS and saved it to my local hard drive. The file contained 21,061 subjects and slightly more than 1,000 variables for these subjects, 8.8% of whom were subsequently admitted to the hospital. These were filtered from the file leaving 19,217 subjects. This file of only discharged visitors was saved as the working file for the descriptive statistics and the logistic regression analyses in this study.

As presented in Table 1, the working file contained a slightly higher percentage of female patients (55.4%) than male patients (44.6%). With respect to race, the majority of the subjects were White (72.9%), while 23.8% were Black and 3.3% were considered neither White nor Black. According to Figure 7, the age distribution was bimodal, with clients who were a year or younger having the highest frequency, followed by those in the mid to late 20s with the second highest frequency peak. As seen in Table 1, the largest age group were visitors between the ages of 25 and 44 years (29.9%); followed by those between 45 and 64 years (21.1%) as the second largest. Children younger than 15 years of age accounted for 19.1% of the sample, and those between 15 and 24 years made up 16.0% of all the ED visitors surveyed. The oldest group (over 65 years) totaled only 13.1% of the sample size. The age ranged from infants (less than a year old) to 93 years of age, with an average age of approximately 36 years, with a standard deviation of 23.238.

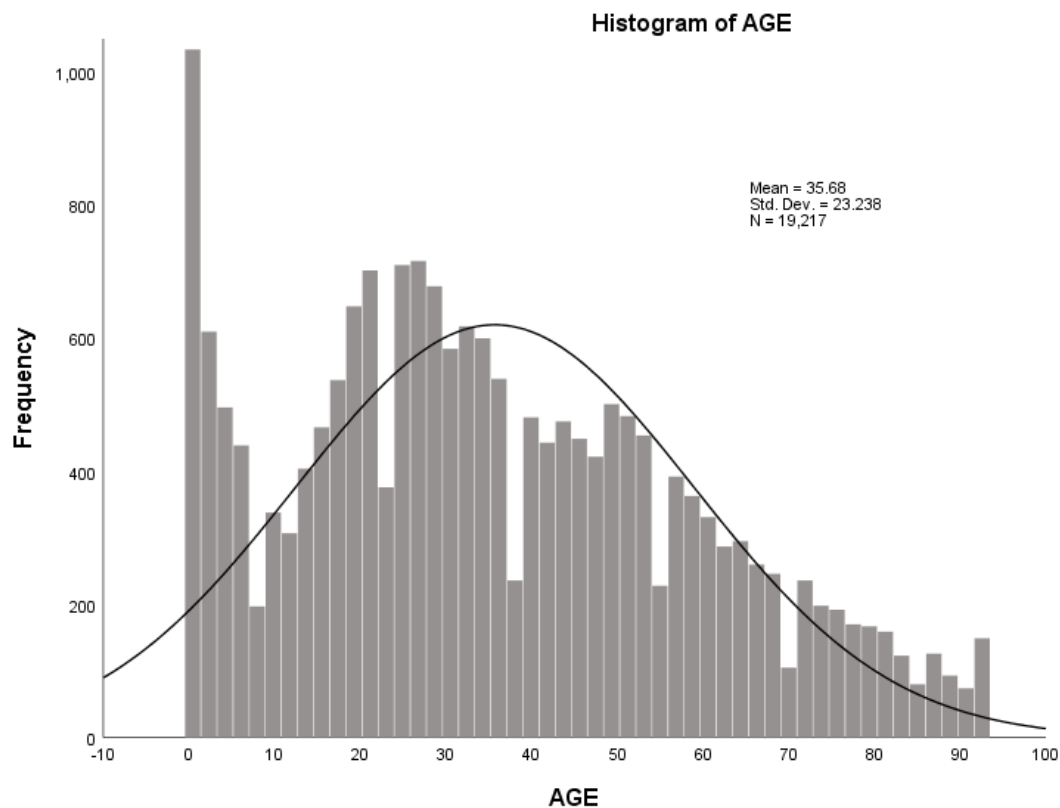


Figure 7. Histogram of AGE distribution.

The geographical distributions were divided into the four main regions of the United States, listed in order of decreasing percentage: 34.2% from the South, 26.3% from the Midwest, 19.9 % from the Northeast, and 19.6% from the West. These numbers were based on the locations of the hospitals themselves and not necessarily the origin of the patients. Of all the EDs included in this study, the majority were located in an area considered metropolitan (83.6%) while less than a quarter were in nonmetropolitan areas (16.3%). These numbers are reflective of the distribution of EDs across the United States.

Table 1

Patient Demographics

Variable	Frequency	Percent	Cumulative percent
Age			
<15	3825	19.9	19.9
15 – 24	3068	16.0	35.9
25 – 44	5741	29.9	65.7
45 – 64	4057	21.1	86.9
65 – 74	1193	6.2	93.1
>= 75	1333	6.9	100.0
Sex			
Female	10639	55.4	55.4
Male	8578	44.6	100.0
Race			
White	14004	72.9	72.9
Black	4578	23.8	96.7
Other	635	3.3	100.0
Region			
Northeast	3820	19.9	19.9
Midwest	5057	26.3	46.2
South	6580	34.2	80.4
West	3760	19.6	100.0
Metro			
Metropolitan	16089	83.7	83.7
Nonmetropolitan	3128	16.3	100.0

Predictor Variables

Independent variable: provider type. The main predictor variable under investigation in this study was provider type, which refers to the different types of medical professionals who are qualified to prescribe medications to patients visiting the ED. Table 2 includes information on the number and types of providers in the analysis.

Table 2

Prevalence of Provider Type

Variable	Frequency	Percent
NOPROVID		
Yes	60	0.3
No	19157	99.7
ATTPHYS		
Yes	16419	85.4
No	2798	14.6
RESINT		
Yes	1583	8.2
No	17634	91.8
CONSULT		
Yes	1374	7.1
No	17843	92.9
RNLPN		
Yes	17828	92.8
No	1389	7.2
NURSEPR		
Yes	1424	7.4
No	17793	92.6
PHYSASST		
Yes	2518	13.1
No	16699	86.9
EMT		
Yes	902	4.7
No	18315	95.3

Of the five types, the attending physician (ATTPHYS) was the most common, with 85.4% of all the patients seen by this provider type. There was considerable overlap as many patients were seen by more than one provider. A physician assistant (PHYASST) was reported for 13.1% of the patients, a nurse practitioner (NURSEPR) for 7.4%, a resident intern (RESINT) for 8.2%, and a consulting physician (CONSULT) visited 7.1% of all the patients. There was a small number (0.3%) of patients for whom no provider was reported (NOPROVID) and almost every patient was initially seen by an RN or LPN (92.8%) or an EMT (4.7%) prior to a visit from the designated ED provider. The information for each of these provider types were saved as separate dichotomous categorical variables in the original data set. This format was preserved and used as is for the logistic regression analyses in this study.

Potential moderators: payment and race. Two specific potential moderators have been identified in this study- Payment source and race of each visitor. The payment type variable (PAYTYPER) is based on six main categories of payment options recorded for ED patients as well as those with no payment record. According to the data set (See Table 3) the largest category of ED clients was made up of Medicaid or CHIP, which combined for 33.3% of recorded payment source. Private Insurance was used by 29.6% of the patients; Medicare used by 15.5%; 9.5% of the clients opted for Self-Pay; and only 0.8% had Worker's Compensation. The rest of the patients was made up of those designated as Charity (0.6%), Other (2.1%), Unknown (6.7%) and Blank (2.0%). This variable though categorical in effect, was treated as scale based on a hierarchy as assigned by data owners, i.e. the CDC statisticians. It was evaluated as both a categorical

variable and an ordinal/continuous variable in this study.

The RACE variable was recorded several ways in the data, but only the variable with three categories were used. These categories were White (Caucasian), Black (African American and of African descent) and Other (those who were neither White nor Black). The other variables recorded provided more specific details about ancestry and ethnic origins, but those were not used as they did not add value to the study. The distribution of the RACE variable was discussed previously (White 72.9%, Black 23.8%, and Other 3.3% Other) in the ‘Demographics’ section.

Table 3.
Prevalence of Payment Type

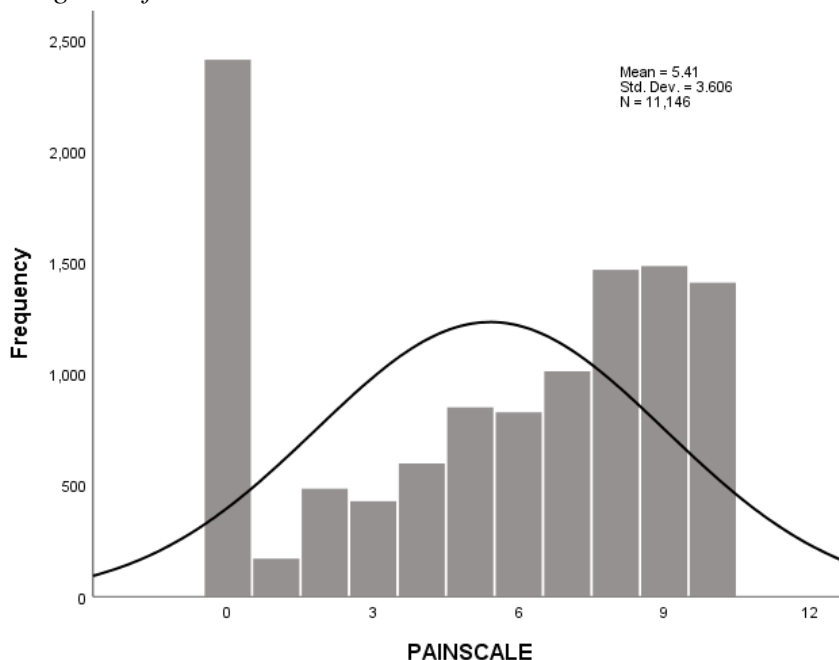
		Frequency	Percent	Cumulative Percent
Valid	Private Insurance	5625	29.3	29.8
	Medicare	2968	15.4	45.6
	Medicaid/CHIP	6402	33.3	79.6
	Worker's Comp	153	.8	80.4
	Self-Pay	1820	9.5	90.0
	Charity	113	.6	90.6
	Other	399	2.1	92.7
	Unknown	1367	7.1	100.0
	Total	18847	98.1	
Missing	Blank	370	1.9	
Total		19217	100.0	

Confounding variables: pain and immediacy. The other confounding variables, besides AGE and SEX, which were included in the model were those that reflected the patient triage determination following evaluation in the ED. The two variables chosen were the one measuring the patient’s pain scale (PAINSCALE) and the other recording

the immediacy with the patient should be seen (IMMEDR). The first triage variable- PAINSCALE variable was collected on numerical scale 0 to 10, as a record of the level pain the patient was experiencing at the time of their visit. The '0' represented no pain, a '3' mild pain, a '5' moderate pain, a '9' severe or intense pain, and a '10' represented unbearable pain. The distribution for the pain scale was bimodal (See Figure 8), with the largest group of patients (21.6%) reported no pain. The next two largest groups were those with the of '8' and '9' pain rating, representing 13.3% and 13.2% respectively. Despite this apparent skewness, approximately half (51.8%) were at '6' or less and the remaining values were above the average rating on the pain scale, approximating the distribution as normal. The average pain rating was 5.13, with a SD of 3.668, with a range between 1 and 10 (Table 4).

Figure 8

Histogram of PAINSCALE distribution

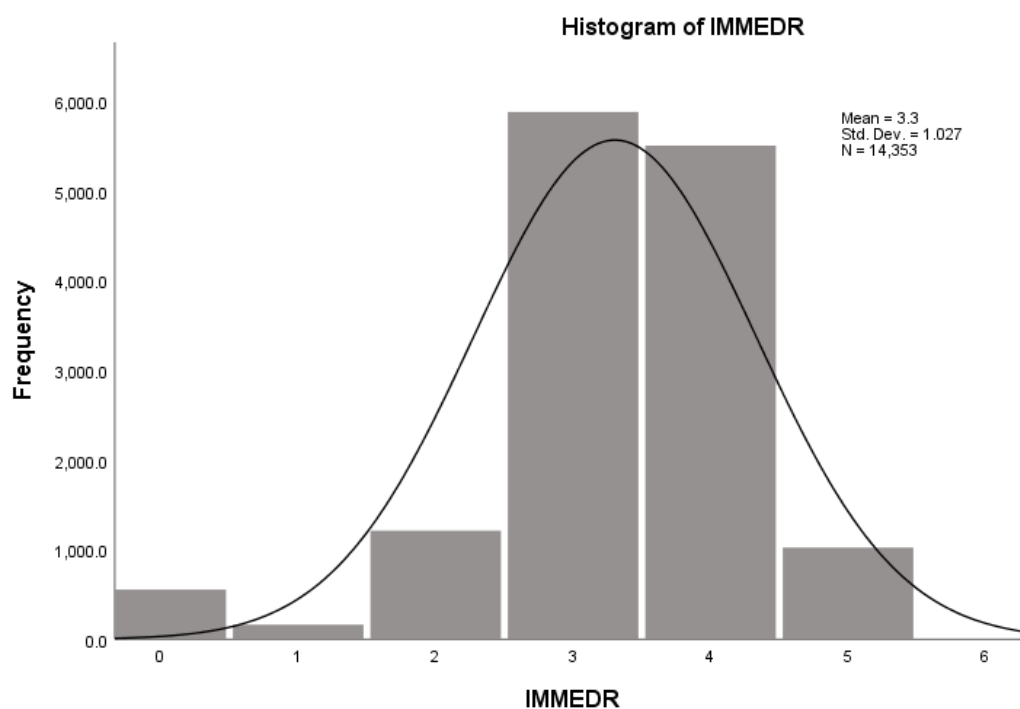


The second triage variable was the IMMEDR, which recorded the immediacy with which the patient should be attended to. It reflected the seriousness of their injury or the intensity of the ailment and was based on the predesignated item triage levels. This variable used a scale 0 to 5: 0=no triage, 1=immediate, 2=emergent, 3 = urgent, 4 = Semi-urgent, and 5 = nonurgent. For the fields without usable data other numbers were assigned: 7 = no triage conducted, -9 = blank, and -8 = unknown). This variable was also used as a normally distributed, continuous variable in the logistic regression analyses, with an average rating of 3.30 and a SD of 1.027 with a range from 1 to 5 (Table 4).

Table 4.
Descriptive Statistics of Confounder Variables

	Mean	STD Dev	Min	Max
AGE	35.68	23.238	0	93
PAINSCALE	5.13	3.668	0	10
IMMEDR	3.30	1.027	0	5

Figure 9
Histogram of IMMEDR (Immediacy) distribution



Dependent Variable: Opioid Prescription Outcome

The outcome variable was the first new variable to be created and this was done using programming code provided by the CDC that allowed the counting of the opioids (classified as “narcotic analgesic”) administered from all 30 of the columns where prescribed medications were recorded. The code was based on the Multum Consumer Drug Code coding system used in all clinic and hospital setting across the country. Frequency analysis (Table 5) of this variable (Opioid_Pres), showed that 24.1% (4,623) of the ED visitors (of the total N=19,217) were prescribed at least one opioid drug. Of those receiving opioid prescriptions, 18.5% (3555) received only one opioid prescription;

4.9% (937) received two opioid prescriptions, 0.64% (122) received three opioid prescriptions, and only 0.05% (9) received four opioid prescriptions during their ED visit.

Table 5.
Opioid Prescription Distribution

		Frequency	Percent	Cumulative Percent
No		14594	75.9	75.9
Yes		4623	24.1	100.0
<i># of Opioid prescribed</i>	1	3555	18.5	94.4
	2	937	4.90	99.3
	3	122	0.64	99.95
	4	9	0.05	100.0
Total		19217		

Bivariate Analysis

Pearson correlation. To investigate the possible correlation violations between the confounders and the predictor variables, a series of bivariate analyses were conducted. For the continuous variables (AGE, TRIAGE, PAINSCALE, and PAYTYPER), a multivariate Pearson correlation test was conducted. The results indicated that there was a significant correlation between all of the variables ($p < 0.001$) with the exception of the correlation between AGE and IMMEDR ($p=0.188$). However, despite statistical significance, all the correlations were weak with a less than 0.1 coefficient value. For example, the strongest correlation was between AGE and PAYTYPER, but the Pearson coefficient measured at only -0.099, indicating a weak negative correlation (Table 6).

Table 6
Correlations of Continuous Variables

Correlations		AGE	IMMEDR	PAINSCALE	PAYTYPER
AGE	Pearson Coefficient	1	-.010	.028**	-.099**
	<i>p</i> -value		.188	.001	.000
IMMEDR	Pearson Coefficient	-.010	1	-.026**	-.046**
	<i>p</i> -value	.188		.002	.000
PAINSCALE	Pearson Coefficient	.028**	-.026**	1	.071**
	<i>p</i> -value	.001	.002		.000
PAYTYPER	Pearson Coefficient	-.099**	-.046**	.071**	1
	<i>p</i> -value	.000	.000	.000	

Chi-square analysis of association. Even though, PAYTYPER is considered a scale variable by the owners of the dataset, it was tested as both a categorical and as a continuous variable for the purposes of correlation analyses. The Chi-square statistical analysis of PAYTYPER was used to investigate its correlation with SEX and RACE. The results (Table 7) indicated that there was a statistically significant relationship with both RACE ($\chi^2 = 510.264$, $p=0.00$) and SEX ($\chi^2 = 113.087$, $p=0.00$). The measure of the effect size, based on the Cramer's V values (0.078 and 0.116), indicate both correlations can be considered weak, but the latter being the strongest of all the bivariate associations measured in this study (Kim, 2017).

The final set of bivariate associations tested were the correlation between the provider types and all the confounders and the potential interaction variables (Table 8). Here again the results indicated that most of the variables bore a statistically significant association ($p < 0.001$). The exceptions were the association between SEX, and four of

the provider-types (ATTPHYS, CONSULT, NURSEPR and PHYSASST) as well as the association between RACE and PHYSASST, which were not statistically significant, and with $p > 0.05$ in each these cases.

Table 7
Chi-Square Analysis of Association

Variable	χ^2	p value	Cramer's V
PAYTYPER			
SEX	113.087	.000	.078
RACE	510.264	.000	.116

The majority of correlations were statistically significant, with most of the covariates (AGE, RACE, PAYTYPER, IMMEDR and PAINSCALE) having an associated with all five provider-types. Of the 30 paired associations tested, 26 were statistically significant and 4 were not as seen in Table 8. The association between SEX and the three provider-types- PHYASST, NURSEPR or CONSULT were not statistically significant ($p=0.283$, $p=0.725$ and $p=0.749$ respectively), and similarly neither was the association between RACE and PHYASST ($p=0.834$). All other correlations were statistically significant with p-values less than 0.05, most of which were also less than 0.001.

Despite the extensive bivariate correlation demonstrated in the Chi-square analyses results strength of the association was weak in all of the cases. The measures of the respective Cramer's V values for each these associated pair were less than 0.100, except for two associations, that between the triage IMMEDR and ATTPHYS, and IMMEDR and PHYSASST. In either case, the Cramer's V values were only 0.142 and

0.109, which is still considered relatively weak associations. Based on these results, the assumption of no or very little multicollinearity among the covariates is met (Kim, 2017).

Table 8

Chi-Square Analysis of Association

Variable	χ^2	p value	Cramer's V
ATTPHYS			
AGE	106.060	.000	.074
SEX	4.225	.040	.015
RACE	27.175	.000	.038
PAY	141.375	.000	.087
IMMEDR	386.716	.000	.142
PAINSC	26.209	.003	.044
RESINT			
AGE	84.069	.000	.066
SEX	12.227	.000	.025
RACE	121.221	.000	.079
PAY	45.755	.000	.049
IMMEDR	188.782	.000	.099
PAINSC	55.276	.000	.064
CONSULT			
AGE	57.386	.000	.055
SEX	0.102	.749	.002
RACE	23.055	.000	.035
PAY	42.229	.000	.047
IMMEDR	155.506	.000	.090
PAINSC	20.954	.021	.039
NURSEPR			
AGE	27.128	.000	.038
SEX	0.124	.725	.003
RACE	41.393	.000	.046
PAY	45.909	.000	.049

IMMEDR	110.632	.000	.076
PAINSC	24.148	.007	.042
PHYSASST			
AGE	37.200	.000	.044
SEX	1.153	.283	.008
RACE	0.363	.834	.004
PAY	42.585	.000	.048
IMMEDR	228.131	.000	.109
PAINSC	27.557	.002	.045

Results

Research Question 1: Provider Type Variation

RQ 1: Is there a significant association between ED provider type and rate of opioid prescription in the ED?

As with all the research questions, a multivariate binary logistic regression, with opioid prescription as the binary outcome, was used to answer this question. Addressing the question involved a three-step process to the building the final model. In the first step, the main confounders were 'AGE,' 'SEX,' 'PAINSCALE,' and 'IMMEDR' were tested for their predictive relationship to the outcome. These four variables were tested to determine which ones should be included in the final model. Based on this preliminary test, it was determined that AGE ($p = 0.000$) and PAINSCALE ($p = 0.000$) were statistically significant and should be included in the model (Table 9). The results indicated that IMMEDR ($p = 0.298$) and SEX ($p = 0.245$), were not a statistically significant predictor of opioid prescription outcome and they were excluded in subsequent models (Table 5).

Table 9.

Odds Ratio of Possible Confounders for likelihood of an Opioid Prescription

	Odds Ratio	p-value	95% C.I.	
			Lower	Upper
AGE	1.018	.000	1.016	1.020
SEX	1.051	.245	.967	1.143
PAINSCALE	1.315	.000	1.297	1.333
IMMEDR	1.005	.298	.995	1.016
Constant	.033	.000		

According to this model, every year increase in age corresponds to a 1.8% (OR=1.018; 95% CI 1.016-1.020) increased likelihood of an opioid prescription when controlling for SEX, PAINSCALE, and IMMEDR. And for every increase in unit pain, there is 32% (OR=1.315; 95% CI 1.297-1.333) increased likelihood of an opioid prescription, when controlling for AGE, SEX and IMMEDR.

In the second step in building the model, a second preliminary multivariate logistic regression (MLR) was performed. This MLR model contained only the five provider-type as predictors and the opioid prescription outcome. In this model, without adjustment of the covariates, (Table10), three of the five provider-type proved to be statistically significant predictors of the outcome, all with $p < 0.001$. According to Table 6, there was a statistically significant relationship between Attending Physician (60% increase), Nurse Practitioner (35% increase) and Physician Assistant (40% increase). Two of the provider-types did not demonstrate a statistically significant relationship with the prediction outcome, RESINT ($p=0.555$), and PHYSASST ($p=0.159$).

Table 10.

Odds Ratio of Provider-Types for the likelihood of an Opioid Prescription

	Odds Ratio	p-value	95% C.I. for EXP(B)	
			Lower	Upper
ATTPHYS	1.604	.000	1.435	1.793
RESINT	.963	.555	.849	1.092
CONSULT	1.095	.159	.965	1.242
NURSEPR	1.348	.000	1.178	1.543
PHYSASST	1.399	.000	1.266	1.546
Constant	.196	.000		

The third and final step in answering the first research question, was the final construction of the comprehensive model that included all the predictor variables: provider-types, along with the confounders AGE, and PAINSCALE. Both AGE and PAINSCALE were remained statistically significant when controlling for the provider types and there was an overall statistical difference in the probability of the provider-type. However, in this new adjusted model (Table 11), the three provider types that were significant predictors were ATTPHYS, CONSULT and PHYSASST when controlling for all other variables. According to this model, a patient seen by an Attending Physician had a 50% (OR=1.491, 95% CI 1.297-1.715), by Consultant Physician had a 32% (OR=1.318; 95% CI 1.127-1.542) or by a Physician Assistant had a 32% (OR=1.315, 95% CI 1.162-1.488) higher probability of being prescribed an opioid medication, compared to not being seen by each of these provider types. Based on these findings, the null hypothesis is rejected in favor of the alternative hypothesis: That there is a significant association between ED provider-type and the probability of an opioid prescription.

Table 11.
Odds Ratio of Provider Types for Opioid Prescription controlling for Age and Pain

	Odds Ratio	p-value	95% C.I.	
			Lower	Upper
AGE	1.018	.000*	1.016	1.020
PAINSCALE	1.306	.000*	1.298	1.335
ATTPHYS	1.491	.000*	1.297	1.715
RESINT	.976	.767	.834	1.143
CONSULT	1.318	.001*	1.127	1.542
NURSEPR	1.167	.076	.984	1.383

PHYSASST	1.315	.000*	1.162	1.488
----------	-------	-------	-------	-------

Research Question 2: Provider Type and Race

RQ 2: Is the association between provider type and the rate of opioid prescription influenced by the race of the patient?

H_0 2: The association between provider type and the rate of opioid prescription is not dependent by the race/ethnicity of the patient.

H_a 2: The association between provider type and the rate of opioid prescription is dependent by the race/ethnicity of the patient.

This question attempts to determine if the RACE variable influences the relationship between provider type and opioid prescription. Published research confirms the role ‘Race’ as having a predictive relationship on the probability of opioid prescription. Firstly, the predictive measure of RACE was tested based on the current data set, and the published findings were confirmed by this analysis. A univariate logistic regression with RACE as the independent variable and opioid prescription as the dichotomous outcome, demonstrated that it was statistically significant. Patients from both race classes, Black and ‘Other,’ were shown to have a reduced likelihood, relative to White patients, of receiving an opioid prescription. However, only the reduced likelihood (20% less) for Black patients (O.R. = 0.799; 95% CI 0.737-0.866) was statistically significant (see Table 12).

Table 12.
Odds Ratio of RACE for Opioid Prescription Probability

	Odds Ratio	p-value	95% C.I.	
			Lower	Upper
Reference (White)		.000		
RACE1 (Black)	.799	.000	.737	.866
RACE2 (Other)	.884	.202	.732	1.068
Constant	.335	.000		

When combined with the other confounders from research question #1, RACE remained statistically significant. Blacks had a slightly less (16% reduced) likelihood (OR=0.836; 95% CI 0.770-0.907), compared to Whites, of being prescribed an opioid, when controlling for AGE and PAINSCALE (See Table 13). Both the odds ratio and statistical significance of the other variables (AGE and PAINSCALE) remained the same.

Table 13.
Odds Ration of Race for Opioid Prescription controlling for PAIN and AGE

	Exp(B)	p-value	95% C.I.	
			Lower	Upper
AGE	1.018	.000	1.016	1.020
RACE	.836	.000	.770	.907
PAINSCALE	1.316	.000	1.299	1.335
Constant	.045	.000		

When the RACE variable was added to the model that included the provider-types, and all the other confounders, RACE remained statistically significant. However, according to Table 14, the addition of RACE did have an effect on the predictive relationship of the provider-types that showed a statistically significant relationship with the outcome. The probability of an opioid prescription from an Attending Physician was now at 61% increase (OR=1.613, %95 CI 1.119-203.5), and the predictive relationship of

the other two provider types (formerly significant) were no longer statistically significant. However, despite the persistence of the statistical significance of Attending Physician, the interaction between this variable and RACE (and the other previously significant variables) was not statistically significant. In this case the findings indicated that the null hypothesis should not be rejected as there appears to be no moderation interaction of RACE on the predictive capacity of the provider-types.

Table 14.

Odds Ratio of RACE, Provider types, AGE and PAINSCALE for Opioid Prescription

	Exp(B)	p-value	95% C.I.	
			Lower	Upper
AGE	1.018	.000	1.016	1.020
RACE	.852	.216	.662	1.098
PAINSCALE	1.319	.000	1.300	1.337
ATTPHYS	1.613	.010	1.119	2.325
RESINT	1.019	.814	.869	1.195
CONSULT	1.264	.254	.845	1.891
NURSEPR	1.176	.062	.992	1.394
PHYSASST	1.073	.672	.775	1.486
ATTPHYS by RACE	.943	.655	.728	1.221
CONSULT by RACE	1.035	.811	.780	1.374
PHYSASST by RACE	1.175	.174	.931	1.483
Constant	.029	.000		

Research Question 3: Provider Type and Payment Type

RQ 3: Is the association between prescriber type and the rate of opioid prescription influenced by the patient's "expected source of payment"?

H_03 : The association between prescriber type and the rate of opioid prescription is not influenced by the patient's "expected source of payment".

H_{a3} : The association between prescriber type and the rate of opioid prescription is influenced on the patient's "expected source of payment".

The second moderation variable investigated was that of the type of payment (PAYTYPER) used by the patients to pay for the services received during their visit to the ED. PAYTYPER was tested for possible interaction with the provider-type variables and their relationship with the opioid prescription outcome. Prior to including it as an interaction variable, PAYTYPER was tested alone, as a categorical variable, in a univariate logistic regression analysis and it was determined to be statistically significant ($p = 0.000$) overall. In this univariate analysis (Table 15), the reference category was Private Insurance, and it showed that those using Medicare (0.5% increase), Worker's Comp (46% increase), and Self-Pay (11% increase) were more likely to be prescribed an opioid compared to those using Private Insurance. On the other hand, Medicaid/CHIP (30% decrease) users were less likely of being prescribed opioids. The odds ratio for the other types of payment categories (NOCHARGE, OTHER, UNKNOWN), relative to Private Insurance, was not significantly different.

Table 15.

Odds Ratio of PAYTYPER (categorical) for Opioid Prescription

95% C.I.

	Odds Ratio	p-value	Lower	Upper
PAYTYPER		.000		
Medicare	1.054	.000	.953	1.165
Medicaid/CHIP	.701	.307	.643	.763
Workers Compensation	1.455	.000	1.036	2.044
Self-Pay	1.112	.030	.988	1.252
No Charge/Charity	.931	.077	.605	1.433
Other	.871	.746	.686	1.106
Unknown	.826	.257	.718	.950
Constant	.354	.007		

When the variable PAYTYPER was added (as an ordinal/continuous variable) to the multivariate analysis (Table 16) containing the other confounders, it remained minimally statistically significant. For every unit change in payment type, there was approximately a 3.6% (OR=0.964; 95% CI 0.944-0.984) decrease in likelihood of an opioid prescription, when controlling for AGE, RACE, PAINSCALE. The OR and the *p*-values of all other confounders remained the same.

Table 16.

Odds Ratio for RACE, AGE, PAINSCALE and PAYTER for Opioid Prescription

	Exp(B)	p-value	95% C.I.	
			Lower	Upper
PAYTYPER	.964	.001	.944	.984
AGE	1.018	.000	1.016	1.020
RACE	.844	.000	.777	.916
PAINSCALE	1.317	.000	1.299	1.336
Constant	.051	.000		

In the final model, adding PAYTYPER along with the provider-types and the other covariates, PAYTYPER and the other confounders maintained a statistically

significant relationship with the outcome (see Table 17). Of the provider types, only ATTPHYS ($p=0.000$) and PHYSASST ($p=0.001$) remained statistically significant, CONSULT failed to reach significance ($p=0.106$). However, the coefficients for the interaction term ATTPHSxPAYTYPER was statistically significant ($p=0.014$), but the other interaction terms were not. For patients seen by an Attending Physician, the probability of opioid prescription decreases by 2.9% for every unit change in payment type. From these findings it can be concluded that the null hypothesis can be rejected, and that Payment Type does influence the relationship between Provider Type and the probability of an opioid prescription

Table 17.

Comprehensive Model of Odds Ratio (RACE, AGE, PAINSCALE, all Provider Types, and possible Interaction variable) for Opioid Prescription

	Odds Ratio	<i>p</i> -value	95% C.I.	
			Lower	Upper
AGE	1.018	.000	1.016	1.020
PAINSCALE	1.317	.000	1.299	1.335
ATTPHYS	1.567	.000	1.351	1.818
CONSULT	1.254	.106	.953	1.652
PHYSASST	1.404	.001	1.143	1.725
ATTPHYS by PAYTYPER	.971	.014	.948	.994
CONSULT by PAYTYPER	1.014	.747	.933	1.102
PAYTYPER by PHYSASST	.972	.320	.918	1.028
Constant	.025	.000		

Summary

Several logistic regression analyses were carried out to answer the respective research questions. Before answering the main questions, the role of several confounders (AGE, SEX, PAINSCALE, and IMMEDR) were first investigated for their relationship

with the opioid prescription outcome. The results indicated that SEX was not statistically significant when controlling for the other factors and was not included in subsequent models. For the first research question, the predictive relationship between the provider-type and an opioid prescription outcome was tested. The results indicated that in the model containing all provider types, there was a statistically significant predictive relationship between opioid prescription and three of the provider types. This statistically significant relationship persisted after controlling for AGE and PAINSCALE values (see Table 11). Patients seen by an Attending Physician (50% increase), Consulting Physician (32% decrease) and Physician Assistant (32% increase) all had an increased likelihood of receiving an opioid prescription, relative to not being seen by these provider types.

The second and third research questions investigated the impact of two possible moderation interactions. The second question dealt with the RACE variable, which proved to be a significant predictor, with Blacks being 28% less likely to receive opioid prescription compared to White patients. However, RACE did not have an impact on the relationship between the Provider Type and the outcome, as the odds ratio and significance remained the same after the addition of RACE (see Table 14). The third question looked at the role of PAYTYPER, and similar to RACE, this variable was predictive of an opioid prescription. Relative to Private Insurance, patients using Worker's Compensation, Self-Pay and Medicare were more likely to be prescribed an opioid (46%, 11%, and 5% respectively). Additionally, when PAYTYPER was introduced into the comprehensive model, which included the provider types, the interaction between Attending Physician and Payment Type was statistically significant,

indicating that this variable does influence the relationship between Provider Type and the probability of an Opioid prescription.

Chapter 5: Discussion, Conclusions, and Recommendations

Introduction

The opioid use disorder is one the most serious aspects of the widespread abuse of prescription drugs in the United States. This problem has been addressed from several angles by those in the public health arena. One of the areas of focus is the variation in prescription rates with regards to opioid analgesics. In this study, I focused on the variation in prescription rates as seen in the many EDs across the country. Public health experts have implicated this variation in the problem of excess opioid flooding the market.

There are many factors involved in the probability of an opioid prescription, and several researchers have looked at various patient characteristics (i.e. race, gender, locale, SES, etc.; see Hui Chen, Hedegaard, & Warner, 2014; Joynt et al., 2013; Mcdonald et al., 2012; Singhal et al., 2016; Tamayo-Sarver et al., 2003). However, more recent researchers have focused on the role of the providers who make prescription decisions and the many provider specific characteristics involved (see Mazer-Amirshahi et al., 2016; Ringwalt et al., 2015; Sasson et al., 2018; Smulowitz et al., 2016). These few studies have all been limited in scale and scope, with relatively small samples sizes. Nonetheless, they have documented prescription rate variation among providers, and they have shed light on a possible source of and potential solution to the opioid prescription dilemma.

In this current study I looked more closely at the role of provider type in opioid prescription variation in the ED setting. The availability of the NHAMACS data set

facilitated this study, which was on a larger scale than previous studies. Not only is this data set a nationwide survey, it contains an excess of information on each ED visit (over 1,000 variables), including all the providers seen and all the drugs prescribed, as well as other demographics such as age, gender, and pain scale score. For this study, I conducted a quantitative analysis of the most recent and available data, the 2015 version of the NHAMACS data set, to answer the study's three research questions.

I designed the research questions to evaluate to what extent, if any, provider type was related to the likelihood of an opioid prescription. The dependent variable was the probability of an opioid prescription, for which I created a dichotomous variable (1 = *opioid prescription*, 0 = *no opioid prescription*) from the analysis of all the prescription drug data available for each visit to the ED. The dependent variables were the five different types of ED providers (attending physician, consultant physician, resident intern physician, nurse practitioner, and physician assistant) who were associated with the patient's prescriptions. These variables were also measured dichotomously (1 = *specific provider seen*, 0 = *specific provider not seen*). The other ED provider types (registered nurse, licensed practical nurse, and emergency medical technician) with no prescribing privileges were not included in the analysis.

In order to elucidate the extent of the association between the dependent variable (probability of an opioid prescription) and the independent variable (provider types), I performed a quantitative analysis to build a predictive model. The outcome variable, being dichotomous, required a logistic regression analysis. Other covariates were added, after being tested and their statistically significant association confirmed. Following the

descriptive analyses, the univariate and multivariate logistic regression analyses generated predictive models that combined the predictors with the outcome to answer the three research questions.

Interpretation of the Findings

Descriptive Statistics

Before I undertook the specifics of the logistic regression analyses, I generated a number of descriptive statistics. All analyses (descriptive and inferential) were conducted after filtering out those who were eventually admitted into the hospital as a result of their visit. This was done to exclude hospital-administered medication from the analysis, as the focus was on discharge prescription. The resulting data revealed that there was relative balance across the genders (55.4% females), with only slightly more males presenting to the ED among those discharged. The distribution of the races was unequal, as was expected based on the national distribution; however Blacks made up 23.8% of the ED visitors' population (compared to Whites, 72.9%, and Other, 3.3%) even though they only make up approximately 13% of the general population. Both the gender and age distribution were similar to those reported in previous national ED studies (Kea, Fu, Lowe, & Sun, 2016b; Mazer-Amirshahi et al., 2014; National Center for Health Statistics, 2017).

The spread in age was more complicated, with the probability distribution revealing a bimodal distribution. The patients under the age of 1 (babies) and toddlers made up the group with the highest frequency, and the rest of the sample made up another group, peaking at around age 22 and 28 years. Previous researchers either

restricted their analysis to adults (more than 18 or 21 years old) or grouped all those younger than 18 years into one category (Kea et al., 2016b; Kilaru et al., 2014; National Center for Health Statistics, 2017).

The main variable in this study was the probability of opioid prescription, which was measured dichotomously. The overall average percentage receiving an opioid prescription at discharge was 24.1% of all ED patients. In other smaller studies of note, researchers reported different opioid prescription rates; in one study, the authors found only a 14% opioid prescription rate in the EDs across three military hospitals (Ganem et al., 2014). In a multicentered study in 2012 consisting of 27,516 patients, the opioid ED prescription rate was 17% (Hoppe et al., 2015). But these studies were not on a national level, present study's percentage (24.1%) is down from the 28% in 2010-2011, but still not as low as the 20% in 2000-2001 (Mazer-Amirshahi et al., 2016) or the average 18.7% during 2006 to 2010 period (Kea et al., 2016b).

For the main independent variables of interest, provider type, an overwhelming majority of the patients were seen by an attending physician (85.4%). The other provider types saw no more than 10% of the sample of patients each (resident intern: 8.2%, a consulting physician: 7.1%, a nurse practitioner: 7.4%, and physician assistant: 4.7%). In a previous study conducted at a single institution and with the providers divided into two categories, MDs and NPs/PAs, researchers recorded comparable percentages: 80% and 20%, respectively (Smulowitz et al., 2016). Similar ratios were recorded in a study that included EDs of three tertiary care military hospitals: MDs, 79%, and PAs, 19% (Ganem et al., 2014). However, the authors of these studies used chart patient-specific data and

were able to associate a specific provider with each patient and each opioid prescription. In this present study, even though the percentages are comparable to previous findings, there was considerable overlap as patients sometime saw two and three ED providers during the same visit; findings should therefore be interpreted with caution.

Research Question 1: Provider Type Variation

The first logistic regression analysis revealed that the probability of an opioid prescription was dependent on age as was reported previously (Dorn, Meek, & Shah, 2011; Weiss et al., 2014; Yacisin et al., 2018). Additionally, as should be expected, the level of pain (PAINSCALE) also had a significant impact on the frequency with which an opioid was prescribed. Previous researchers did not include level of pain as a covariate; they either restricted their study to a specific pain-related condition (e.g. low-back pain or abdominal pain; Dorn et al., 2011; Mazer-Amirshahi et al., 2014; Patel & Afshar, 2017) or categorized a patient's pain based on predetermined diagnostic categories (R. Dickason et al., 2015; Joynt et al., 2013; Kea et al., 2016b; Prunuske et al., 2014). Interestingly, in the analysis data disclosed that 7.5% of those with a reported pain level of *zero* were recorded as having been prescribed an opioid analgesic. This is possibly due to an error in documenting the patient's actual pain score or failure to update the information after the pain level changed.

In this data set, neither the effect of gender nor that of triage level (IMMEDR) proved to be statistically significant. In other research, where gender was reported as significantly different, the effect sizes were small- 53% of male vs 42% female, (Kea et al., 2016a) or male 50% vs female 47 % (Hoppe et al., 2015). Like in this present study,

the reports of significant differences were based on unadjusted analysis, and once adjusted, the gender difference was no longer statistically significant (Dorn et al., 2011)(R. M. Dickason et al., 2015)(Gebauer et al., 2017). Similarly, as with the gender variable, when the model was adjusted for pain score, the measure of triage was no longer statistically significant. These are both positive findings, indicating that there is not gender disparity in the opioid prescribing rates, and that the rates of prescribing this pain-medication are associated more strongly with pain levels than with triage measures.

ED provider type variation. In the comprehensive model developed from this data set, the three provider-types with statistically significant predictive association, all with an increased probability of an opioid prescription, were Attending Physician (60%), Consultant Physician (35%) and Physician Assistant (40%). It is worth mentioning, that one other provider-type had a potentially significant relationship to the outcome, that of Nurse Practitioner. The relationship was not significant in the univariate formula, but when adjusted for age, the p -value was markedly reduced from 0.261 to 0.068, almost approaching significance (see Table 18). Similarly, with that of Consultant Physician, which originally was marginally statistically insignificant in the univariate model, became unquestionably significant ($p=0.000$) when controlling for pain. These results suggest a difference in the influence of the covariates, age having a greater impact (relative to pain) on the Consultants, and inversely, pain being more critical (relative to age) to the Nurse Practitioner with respect to prescribing opioids. A previous pilot study on the factors affecting ED providers' opioid prescription decisions similarly reported that patients' pain level was higher in the order of importance for advance practice

providers (NPs/PAs) than for Resident and Attending physicians. On a scale of 1-5, attendings ranked pain 2.99 on average and 2.89 for Residents, but 3.60 for the NPs/PAs group (Pomerleau et al., 2016).

Ultimately, in the final model for the current analysis, the Nurse Practitioner variable was excluded and that of the Consultant retained, as was warranted by the corresponding *p*-values after adjusting for both Pain and Age (See Table 1). When considering these values, it is important to bear in mind the overlap in the data (patients seen by more than one provider) and that attending physicians (85.4%) saw between 12 to 6 times as many patients that all the other types of providers (7.1% and 13.1%). This overlap introduces a measure of correlation that serves to dilute the accuracy of the results, but it should be noted that these odds values were approximately the same in the univariate logistic regression and when adjusted for age and painscale.

Table 18

Adjusted and Unadjusted *p*-values for Nurse Practitioner and Consultant Physician

	Unadjusted	Age	Pain	Race	Age + Pain
Nurse Practitioner	0.261 (1.074)	0.068 (1.125)	0.278 (0.918)	0.221 (1.081)	0.620 (0.961)
Consultant Physician	0.072 (1.122)	0.593 (1.035)	0.000 (1.418)	0.050 (1.134)	0.000 (1.340)

In most of the studies on the variation in opioid prescription rates in the ED, researchers used categorizations other than the different provider types used in the current study. In most studies researchers looked at only MDs, comparing experienced vs

inexperienced emergency physicians; or divided the providers into low-intensity prescribers versus high-intensity prescribers. Few studies stratified based on provider types, like the military two-hospital study, where researchers found that the PAs were more than twice as likely to prescribe opioids (relative to non-opioids) than MDs were, with opioids being 55% and 23% of their respective total analgesic prescriptions (Ganem et al., 2014). Those results echo that of the national multi-year trend (2005 to 2015) study on opioid prescriptions rates, where researchers found that opioid prescriptions by MDs and PAs increased by 61% on average, but the increase was twice as much for Nurse Practitioners, increasing 116.7% over the same period (Yang et al., 2018). Another related study of the opioid prescription for Medicare patients found an overall significant rise in opioid prescriptions, but the increase was greater for by the advanced practice practitioners (APPs) compared to the that for the MDs (Axeem, 2018). These results confirm the increasing roles and responsibilities for APPs, not just in medicine in general but in prescribing of medication, particularly opioids.

Research Question 2: Provider Type and Race

Race was found to be a significant predictor of the probability of an opioid prescription with Blacks (20% less unadjusted or 17% less adjusted) less likely to be prescribed an opioid and this is line with many of the previous studies. This is congruent with the findings in other study (Singhal et al., 2016) (Joynt et al., 2013) (R. Dickason et al., 2015). One of the earliest on this topic, reported that despite the trending (1993 to 2005) increase in opioid prescription in the EDs, racial difference persisted, with the increase for Whites going from 31% to 40%, while increasing from 23% to 32% for

Blacks (Pletcher, 2008). A later study looking using NHAMCS data from 2007 to 2011, found that the racial/ethnic variation in opioid prescription rate had worsened, with Blacks being less likely (43% for abdominal pain and 33% for back pain) to receive an opioid prescription compared to Whites and other races (Singhal et al., 2016).

Additionally, the racial disparity between Whites and Blacks for the frequency of opioid prescription worsened as the pain intensity increased, e.g. back pain (48% vs 36%, respectively), headache (35% vs 24%), abdominal pain (32% vs 22%), and other pain (40% vs 28%) (Pletcher et al., 2008). The many studies exposing and confirming the racial disparity over the years may have something to do with the reduced percentage numbers reported in the current analysis, nonetheless the disparity persists.

When added to the model, race has an effect on the strength of the relationship for two of the providers (N.P. and P.A.), but not the other Attending. For the N.P., the odds decreased from 35% to 17% and the new *p*-value failed to reach significance ($p=0.062$), while in the case of the PAs, the odds decreased to almost one 1 ($OR=1.073$), and it was no longer statistically significant ($p=0.672$). Since the interaction terms for each of three provider types were not statistically significant the null hypothesis was not rejected, nonetheless that does not rule out the effect of RACE on the relationship between these provider types and the outcome. Maybe the effect of race is not one of moderation but one of mediation, and this would be confirmed or refuted by a different type of analysis.

Racial disparity in US healthcare system is been studied and reported on for decades, and this disparity has been reflected in the treatment of pain and specifically in the administration of analgesics (Chen et al., n.d.; Committee on Advancing Pain

Research, Care, 2011; R. M. Dickason et al., 2015; Jeffery et al., 2018; Maly & Vallerand, 2018). As in other areas of healthcare, there have been many speculations as to the cause of this racial disparity, including physicians being majority White and empathizing best with patients who look like them; to the minimizing of the pain being reported by Black patients; or reduced ability of providers to identify signs of potential abuse in White patients (Chen et al., n.d.). Interestingly, another study of 5.2 million opioid prescriptions (Optimum Labs Data Warehouse 2009-2015) found similar results in the racial disparity, but when the prescriptions were stratified by types, Blacks more likely than other racial groups to receive the short term, lower dose prescriptions while Whites received longer term, higher dose opioid prescriptions (Jeffery et al., 2018)(Joynt et al., 2013). Another study reported on the “reverse disparity” in the offering of opioid monitoring and treatment strategies, Whites being more frequently exposed and directed to treatment once opioid abuse disorders are suspected (Beker et al., 2011). Despite reports on the racial disparity, the racial disparity in prescription and treatment, remains correlated with the predominance of Whites in long term use and even abuse of opioids (Barnett et al., 2017; (Hui Chen et al., 2014; National Academies of Sciences, Engineering, and Medicine, 2017).

Research Question 3: Provider Type and Payment Type

One of measures that is always difficult to assess is that of the patient’s socioeconomic status, as that type of data is not usually collected directly in these types of surveys. Most studies have used neighborhood-level socioeconomic status as defined by the patient’s zip code (Hudley et al., 2014)(Gebauer et al., 2017), but this is not always a

reliable indicator as many neighborhoods are of mixed of socioeconomic. Like other studies, this study used payment source as a pseudo-SES measure to evaluate the predictive relationship between the opioid prescription outcomes. The idea of SES being reflected in payment source is not new, as other studies have used it and found similar variation in prescription rates based on this pseudo-SES classification (Dorn et al., 2011; Singhal et al., 2016; Sites et al., 2014).

The analysis of the NHAMCS 2015 data found that there was a predictive relationship between this pseudo-SES and the probability of an opioid prescription. Worker's Compensation users had the highest increased (45.5% relative to Private Insurance) all the three payment types with an increased likelihood. The other two were Medicare and Self-Pay, but the effect sizes were marginal (5.4% and 11.2%, respectively). The remaining payment types had reduced likelihoods, and the differences were not statistically significant. Worker's Compensation being associated with a higher likely to obtain the prescription medicine compared to other types of insurance or payment source was reported previously. Hoppe et al. reported that, when Worker's Compensation was used as the reference, all other payment types had a reduced odds of prescription opioid, Federal/Government 0.70; Medically Indigent 0.58; Private 0.56, and Self-Pay 0.24 (Hoppe et al., 2014).

Other researchers have also reported on the relationship between opioid prescription rates and socioeconomic status measured by insurance type. But most of these studies used three or four major groupings that included Private Insurance, Government/Public Insurance (Medicaid, Medicare separately or together), and Other (no

insurance, charity, etc.). Although the results of these study would depend on whether a particular diagnosis was being evaluated or opioid prescriptions as a whole. In general, these studies found that patients with public/government (Medicaid or Medicare) insurance were more likely to be prescribed opioids compared to those with private insurance (Shah et al., 2015)(Hoppe et al., 2017)(Joynt et al., 2013)(Dorn et al., 2011). These findings were in agreement with those that used neighborhood socioeconomic measures, and found that low nSES was associated with a higher probability of opioid prescription compared to high nSES, but the racial disparity persisted in either communities (Gebauer et al., 2017) (Prunuske et al., 2014)(Maly & Vallerand, 2018)(Joynt et al., 2013).

Findings Related to the Conceptual Framework

According to SIT, human behavior can be explained by underlying thoughts and subconscious motivations, based mainly one's interpretation of social symbols (Aksan, 2009). In the field of healthcare, SIT enlightens the nature of the relationship between patients and their healthcare providers, and the many factors that govern these unique social interactions. SIT guided research has revealed the importance of the provider's work priorities and their perceptions of their patients as being utmost concerns, especially in the ED where the interactions are shorter and more intense (Battjes, 2009). In these setting, prescription decision making is influenced by the established guidelines and policies, but also by the providers' unconscious notions of the as well. Insight into these unconscious notions are needed to provide guidelines that prevent their adverse effects.

The findings in this study substantiates the prescription rate variation based on provider types as is presumed by idea inherent in SIT. The different provider types, though all with similar objectives, have differences in their training, their approach, their attitudes and their practice of healthcare (Maycock, 2015). According to SIT it is these differences that will have an impact (directly or indirectly) on their health care decisions, which in turn affects their prescription decision making and ultimately their prescription rates (Byrne & Heyman, 1997). These differences however have the potential to put patients at risk for undertreatment or overtreatment when it comes to their pain related ailment (Singhal et al., 2016)(Maycock, 2015). It is therefore important that these differences are studied and addressed so that providers can be confident that their actions are in no way jeopardizing the health of those they are serving.

There are a variety of factors involved in the ED prescription rate variation for opioids. Previous research findings have reported on prescription rate variation among the same types of providers and on variation based on race, age, experience, location, etc. Studies that did not divide the providers among the different types, found variations that were based on other physician characteristics. Uncovering the traits that have the largest impact on prescription variation can be important to the practice of pain management specifically and to medicine as a whole. Prescription decisions are complicated for providers, and the chaos in the ED and the stigma surrounding opioids all make for a difficult situation. Providers are often caught in the middle of patient satisfaction and evaluation of them and the policies put in place by those in charge (Sinnenberg et al., 2017). Policies informed by sound reliable research can make things easier for them and

improve the experience for provider and patient, both in the short and long term. The undisputable impact of race and socioeconomics on prescription rate, even after controlling for age and painscale are clear implication that biases are involved. Uncovering and acknowledging these biases are important to fair and balanced treatment for all patients. And confronting these biases may be critical to minimizing the contribution of the providers to the excess of opioids exposure that puts patients at risk for abuse in the future.

Limitations of the Study

This study did find that there were statistically significant differences between the various provider types and the rate of opioid prescription but there are many limitations to the generalizability of the findings. One of the biggest limitations of this type of study is the nature of the data. There is considerable overlap in the variables of interest, provider type. As such it is impossible to determine which provider actually prescribed the medication and the analysis is purely one of association. Additionally, the diagnosis variables also overlap, with many patients many having more than one of the over 25 different main diagnoses, making it challenging to include ‘Diagnosis’ as a variable and thereby control for it.

The effect of both race and payment type were evaluated and the results indicate that both have a predictive relationship to the outcome. However, based on this restricted analysis of prescription rate, only payment time was found to have a significant interaction with the provider type. Other studies have found that race significantly correlated to socioeconomics and consequently to the payment source only more a

detailed data set, and more specific statistical analyses will unravel the nature of the relationship of each to the outcome. Accounting for the possible violations of the assumptions of limited collinearity may provide more reliable results.

One of the assumptions of this study is that an increased prescription rate implicates that provider type as contributing to a problem of over prescribing opioid. However, as other studies have shown, those who prescribe more frequently may actually be more closely following protocol. No comparison of opioid analgesics relative to non-opioid analgesics no information on the appropriateness of the prescription. Interestingly, a small study on the effect of state drug monitoring program found that while residents prescribing habits were influenced by that of their training attendant, one third of the attending physicians who consulted the program resulted in an increase in the quantity or amount of opioid drugs prescribed (Feldman et al., 2012). The assumption was that the Attendings felt safer to adjust their prescription habits to meet the clients need after realizing that it was sanctioned in the official guidelines.

As this analysis did not account for the quantity or dosage of the opioid prescription (information not contained in this data set), there is no determination of that effect relative to overall rate. Also, since there is no data on individual providers or inclusion of detailed diagnosis, it is difficult to make more substantial inferential analysis of the appropriateness or inappropriateness of the prescriptions (Kea et al., 2016b). This study did not identify individual patients, but instead use ED visits as the unit of measure, and it did not distinguish between who received on opioid prescription or several (up to

four) during the visit for any possibility of follow-up. This national data is suitable for determining average effect, but not for the more specific type determination.

Recommendations

The findings in this study is the first of its kind in that it provides a large-scale perspective (on a national level) on the results of opioid prescription variation based on provider types. It also confirms the role of acknowledged covariates age, race, pain scale and payment types, and although the strength of the data lies its size, the results must be inferred with caution. Working with such a large data set can make it difficult to detect the nuances that may lay in the various categories of the variables measured. The findings are based on national averages and should be taken as such. The current results are recommended for comparing past and future national averages and for generating general insights into the nature of the opioid epidemic prescription rate problem.

There are many limitations to this study, but it does provide some direction for future research. The area of opioid rate variation is complex and even when zeroing in on the specifics of provider type variation, there are many issues to be considered. To make the findings more specific, the provider type analyses can be based on a number of different strata, including region, state, type of hospitals or institutions that house the various EDs, size of institution, etc. Other ways that the data can be divided include-comparing patients' demographics (different age groups, diagnosis, race, class, etc.) or time of week (weekday vs. weekends), or daytime vs. night time or other classifications that allow a deeper understanding into of nature of the relationships detected.

Other limitations to the study included the lack of detailed information for provider or patient. Unfortunately, the data collected in the NHAMCS does not provide any information about individual provider characteristics or specifics of the opioid prescription received by patients. Future research is needed into these aspects and for this data other than administration survey data are needed. For a thorough analyses of the role of provider characteristics, information about the provider demographics (age, sex, race and duration of experience) is required, as preliminary research has indicated that this may be more important than provider type (Bartley et al., 2015). For the ED providers, maybe the difference is not in the provider-types but in the type of training and background or the number of years of experience or some other feature or characteristics that affects their prescription decisions. But this can only be assessed using data that collected the relevant information.

Similar to the issue of provider type classification is that of absence of information about the class of opioid prescribed - without information about the class, dosage, strength, duration of the prescription and the actual diagnosis associated, it is difficult to analyze the appropriateness of the prescription. In addition, there the issue of the different types of opioids (hydrocodone, oxycodone, codeine, etc.), as well as immediate release vs. extended release, the number of pills, etc. Another important area of future research has to do with the selective comparison of opioid analgesic relative to the non-opioid analgesic. Here again, these analyses can only be conducted with the appropriate data set and future data collection effort should be duly focused.

There are so many aspects to the Opioid epidemic, that it requires a multi-dimensional approach that involves patients, doctors, APPs, clinics, medical school, insurance companies, hospital administration, etc. This study finding does imply that further research is needed to inform the provider education modules and develop evidence-based protocols to help ED providers in their difficult task of prescription decision making. Research in the area of dose-equivalence, appropriateness of prescription, assessing pain levels, and patient's drug-seeking behavior are all needed as well. Critical to this issue is the collecting of information on the provider's prescribing practice -and its short term and long-term effects on their respective patients- requiring longitudinal as well as patient-specific data. The current study assumes that all the opioid prescribed were done on discharge and not administered in the ED and there is no specification on the method of administration. The absence of this or any follow-up data prevents any study into the possible correlation between the prescriptions and subsequent use diversion or potential abuse disorders.

Implications

Based on reports in the media, the opioid epidemic will be around for some time and research into the many factors involved will also continue. There is much to learn about opioid use and abuse and how it can be avoided and the variation in the prescription rate is an important aspect of the problem. Many studies have generated considerable information on the patient characteristics that contribute to the variation in prescription rates. This study's findings have provided much need additional insight about the conceivable role that ED providers play in the prescription rate variation that

contributes to the opioid over-exposure that is an unfortunate part of pain management. There is more to be uncovered, but the results of this analysis point to evidence of the existing differences that must be acknowledged and addressed.

The importance of communicating these findings to stakeholders should not be overlooked. The providers who deal with pain management in the ED as well as the individual patients and those at risk who use these facilities at one time, or another should be informed. Providers must become cognizant of the effect of their conscious and unconscious biases, through education and information, and be trained in ways that help them overcome these biases. Ideally, ED providers should be made to do training in facilities dedicated to pain management, working with specialists who have experience in dealing with the specifics of this unique field. They should also be made to understand the biases that may be unique to their own training and background (and other yet unidentified characteristics), because only then can they work towards proactively overcoming them. Finally, the ED providers should be assessed specifically on their prescribing rates and this information shared with them, as there can be incongruence between the self-perceptions of their prescription rates and the reality of that rate as is reflected in the records (Bartley et al., 2015).

The findings also point to the need for patients to be more actively involved in the treatment they receive, specifically the type and quantity of prescriptions from the ED providers. These prescriptions are based, in part, on the providers' perceptions of the patients' needs. If the patient fails to adequately communicate their needs, then the treatment can be insufficient or unsatisfactory. When it comes to pain management in the

ED, the providers have to make split second decisions and in this they can be assisted by an informed patient. Patient need to know not just about the potential dangers of abuse of and addiction to opioids, but also about the options that they have for pain management, but also about the disparities and biases that may be subjected to in these settings (Committee on Advancing Pain Research, Care, 2011). The experience of pain varies from one individual to the next, but effective communication can make for a more informed interaction, and therefore a more satisfactory outcome for both providers of care and recipients of such care, and thereby minimize the potential for harm.

Conclusion

The study found that there is significant difference in the prescription rate among the various ED provider type even when controlling for accepted patient traits such as age and level of pain. Race and payment types were also significant predictors of the probability of an opioid prescription, but only the later was found to interact with the provider type variable. These findings were based on the analysis of the NHAMCS 2015 data set and provide an overall insight, but the findings are limited by the nature of the dataset. Ultimately, the problem of opioid prescription variation, in the ED and elsewhere, will require further research to elucidate the nature of the relationships detected and thereby help to minimize the burden of the opioid abuse disorder on the health care system specifically, and our on our society in general.

References

- Agency for Health Care Policy and Research. (1992). Acute pain management: Operative or medical procedures and trauma, Part 2. *Clinical Pharmacy, 11*(5), 391–414. Retrieved from <http://www.ncbi.nlm.nih.gov/pubmed/1582131>
- Aksan, N., Kısac, B., Aydın, M., & Demirbuken, S. (2009). Symbolic interaction theory. *Procedia Social and Behavioral Sciences, 1*, 902–904. <https://doi.org/10.1016/j.sbspro.2009.01.160>
- AMCP Partnership Forum. (2015). Proceedings of the AMCP Partnership Forum: Breaking the link between pain management and opioid use disorder. *Journal of Managed Care & Specialty Pharmacy, 21*(12). Retrieved from <http://www.amcp.org>
- Baehren, D. F., Marco, C. A., Droz, D. E., Sinha, S., Callan, E. M., & Akpunonu, P. (2010). A statewide prescription monitoring program affects emergency department prescribing behaviors. *Annals of Emergency Medicine, 56*(1), 19-23.e3. <https://doi.org/10.1016/J.ANNEMERGEMED.2009.12.011>
- Barnett, M. L., Olenski, A. R., & Jena, A. B. (2017). Opioid-prescribing patterns of emergency physicians and risk of long-term use. *New England Journal of Medicine, 376*(7), 663–673. <https://doi.org/10.1056/NEJMsa1610524>
- Bartley, E. J., Boissoneault, J., Vargovich, A. M., Wandner, L. D., Hirsh, A. T., Lok, B. C., ... Robinson, M. E. (2015). The influence of health care professional characteristics on pain management decisions. *Pain Medicine, 16*(1), 99–111. <https://doi.org/10.1111/pme.12591>

- Battjes, R. J. (2009). Symbolic interaction theory: A perspective on drug abuse and its treatment. *International Journal of the Addictions, 19*(6), 675–688.
<https://doi.org/10.3109/10826088409057214>
- Beaudoin, F. L., Janicki, A., Zhai, W., & Choo, E. K. (2018). Trends in opioid prescribing before and after implementation of an emergency department opioid prescribing policy. *American Journal of Emergency Medicine, 3*, 329-331.
<https://doi.org/10.1016/j.ajem.2017.07.068>
- Beker, W. C., Starrels, J. L., Heo, M., Li, X., Weiner, M. G., & Turner, B. J. (2011). Racial differences in primary care opioid risk reduction strategies. *Annual Family Medicine, 9*, 219-225. <https://doi.org/10.1370/afm.1242>
- Benzies, K. M., & Allen, M. N. (2001). Symbolic interactionism as a theoretical perspective for multiple method research. *Journal of Advanced Nursing, 33*(4), 541–547. <https://doi.org/10.1046/j.1365-2648.2001.01680.x>
- Berridge, V. (2009). Heroin prescription and history. *New England Journal of Medicine, 361*(8), 820–821. <https://doi.org/10.1056/NEJMe0904243>
- Bonfrer, I., Figueroa, J. F., Zheng, J., Orav, E. J., & Jha, A. K. (2018). Impact of financial incentives on early and late adopters among US Hospitals: observational study. *BMJ, 360*, 2018(360), j5622. <https://doi.org/10.1136/bmj.j5622>
- Broida, R. I., Gronowski, T., Kalnow, A. F., Little, A. G., & Lloyd, C. M. (2017). State Emergency Department Opioid Guidelines: Current Status. *Western Journal of Emergency Medicine, 340*(3). <https://doi.org/10.5811/westjem.2016.12.30854>
- Butler, M. M., Ancona, R. M., Beauchamp, G. A., Yamin, C. K., Winstanley, E. L., Hart,

- K. W., ... Lyons, M. S. (2016). Emergency Department Prescription Opioids as an Initial Exposure Preceding Addiction. *Annals of Emergency Medicine*, 68(2), 202–208. <https://doi.org/10.1016/j.annemergmed.2015.11.033>
- Byrne, G., & Heyman, R. (1997). Understanding nurses' communication with patients in accident & emergency departments using a symbolic interactionist perspective. *Journal of Advanced Nursing*, 26(1), 93–100. Retrieved from <http://www.ncbi.nlm.nih.gov/pubmed/9231282>
- Cantrill, S. V., Brown, M. D., Carlisle, R. J., Delaney, K. A., Hays, D. P., Nelson, L. S., ... Whitson, R. R. (2012). Clinical Policy: Critical Issues in the Prescribing of Opioids for Adult Patients in the Emergency Department. *Annals of Emergency Medicine*, 60(4), 499–525. <https://doi.org/10.1016/j.annemergmed.2012.06.013>
- Case, A., Deaton, A., Cutler, D., Skinner, J., & Weir, D. (2015). Rising morbidity and mortality in midlife among white non-Hispanic Americans in the 21st century. <https://doi.org/10.1073/pnas.1518393112>
- Centers for Disease Control & Prevention. (2010). Emergency Department Visits Involving Nonmedical Use of Selected Prescription Drugs --- United States, 2004--2008. Retrieved August 10, 2018, from <https://www.cdc.gov/mmwr/preview/mmwrhtml/mm5923a1.htm>
- Centers for Disease Control and Prevention. (2011). Vital Signs: Overdoses of Prescription Opioid Pain Relievers --- United States, 1999--2008. Retrieved July 6, 2018, from <https://www.cdc.gov/mmwr/preview/mmwrhtml/mm6043a4.htm>
- Centers for Disease Control and Prevention. (2017). NAMCS/NHAMCS - About the

- Ambulatory Health Care Surveys. Retrieved September 18, 2018, from https://www.cdc.gov/nchs/ahcd/about_ahcd.htm
- Centers for Disease Control and Prevention. (2012). Survey Content for the National Ambulatory Medical Care Survey and National Hospital Ambulatory Medical Care Survey, 52.
- Centers for Disease Control and Prevention/National Center for Health Statistics. (2017). Datasets and Documentation: NHAMCS public-use files. Retrieved June 28, 2018, from https://www.cdc.gov/nchs/ahcd/datasets_documentation_related.htm
- Cerner Multum. (2018). Cerner Multum Consumer Drug Information. Retrieved September 20, 2018, from <https://www.drugs.com/mtm/>
- Chapman, C. M. (1976). The use of sociological theories and models in nursing. *Journal of Advanced Nursing*, *1*(2), 111–127. <https://doi.org/10.1111/j.1365-2648.1976.tb00434.x>
- Cheatle, M. D. (2015). Prescription Opioid Misuse, Abuse, Morbidity, and Mortality: Balancing Effective Pain Management and Safety. *Pain Medicine*, *16*(suppl 1), S3–S8. <https://doi.org/10.1111/pme.12904>
- Chen, I., Kurz, J., Pasanen, M., Faselis, C., Panda, M., Staton, L. J., ... Cykert, S. (n.d.). Racial Differences in Opioid Use for Chronic Nonmalignant Pain. <https://doi.org/10.1111/j.1525-1497.2005.0106.x>
- Cheung, C. W., Qui, Q., Choi, S. W., Moore, B., Gouke, R., & Irwin, M. (2014). Chronic Opioid Therapy for Chronic Non-Cancer Pain: A Review and Comparison of Treatment Guidelines. *Pain Physician*. Retrieved from

<https://pdfs.semanticscholar.org/fd33/b2536a9b2bd2ffe42e6fcb60d38f6194d355.pdf>

Cicero, T. J., Ellis, M. S., Surratt, H. L., & Kurtz, S. P. (2014). The Changing Face of Heroin Use in the United States. *JAMA Psychiatry*, *71*(7), 821.

<https://doi.org/10.1001/jamapsychiatry.2014.366>

Cochran, B. N., Flentje, A., Heck, N. C., Van, J., Bos, D., Perlman, D., ... Carter, J.

(2014). Factors Predicting Development of Opioid Use Disorders among Individuals who Receive an Initial Opioid Prescription: Mathematical Modeling Using a Database of Commercially-insured Individuals. *Drug Alcohol Depend*,

138, 202–208. <https://doi.org/10.1016/j.drugalcdep.2014.02.701>

Colliers, R. (2018). A Short History of Pain Management. *CMAJ / JANUARY*, *8*(1).

<https://doi.org/10.1503/cmaj.109-5523>

Committee on Advancing Pain Research, Care, and E. (2011). *Relieving Pain in America: A Blueprint for Transforming Prevention, Care, Education, and Research*. (Institute of Medicine of the National Academies, Ed.). Washington, D.C.: National Academy of Sciences. Retrieved from

http://www.nap.edu/catalog.php?record_id=13172

Csiernik, R. (2016). Substance Use and Abuse: Everything Matters, Second Edition.

Retrieved June 22, 2018, from www.cspi.org

Daum, A. M., Berkowitz, O., & Renner, J. A. (2015). The evolution of chronic opioid therapy and recognizing addiction. *JAAPA : Official Journal of the American Academy of Physician Assistants*, *28*(5), 23–27.

<https://doi.org/10.1097/01.JAA.0000464268.60257.ad>

Dickason, R., Chauhan, V., Mor, A., Ibler, E., Kuehnle, S., Mahoney, D., ... Dalawari, P.

(2015). Racial Differences in Opiate Administration for Pain Relief at an Academic Emergency Department. *Western Journal of Emergency Medicine*, 16(3), 372–380. <https://doi.org/10.5811/westjem.2015.3.23893>

Dickason, R. M., Chauhan, V., Mor, A., Ibler, E., Kuehnle, S., Mahoney, D., ...

Dalawari, P. (2015). Racial Differences in Opiate Administration for Pain Relief at an Academic Emergency Department. *Western Journal of Emergency Medicine*, XVI(3). <https://doi.org/10.5811/westjem.2015.3.23893>

Dorn, S. D., Meek, P. D., & Shah, N. D. (2011). Increasing Frequency of Opioid

Prescriptions for Chronic Abdominal Pain in US Outpatient Clinics. *YJCGH*, 9, 1078-1085.e1. <https://doi.org/10.1016/j.cgh.2011.08.008>

Dubois, M. Y., & Follett, K. A. (2014). Pain Medicine: The Case for an Independent

Medical Specialty and Training Programs. *Academic Medicine*, 89(6), 863–868. <https://doi.org/10.1097/ACM.0000000000000265>

Ellis, & Paul D. (2010). *The Essential Guide to Effect Sizes*. New York: Cambridge

University Press. Retrieved from

[http://www.fb4all.com/download/ebooks/statistics/The Essential Guide to Effect Sizes 2010.pdf](http://www.fb4all.com/download/ebooks/statistics/The%20Essential%20Guide%20to%20Effect%20Sizes%202010.pdf)

Faul, F., Erdfelder, E., Lang Albert-Georg, & Buchner, A. (2007). *G*Power 3: A flexible*

statistical power analysis program for the social, behavioral, and biomedical sciences. Retrieved from

http://www.gpower.hhu.de/fileadmin/redaktion/Fakultaeten/Mathematisch-Naturwissenschaftliche_Fakultaet/Psychologie/AAP/gpower/GPower3-BRM-Paper.pdf

Feldman, L., Skeel Williams, K., Knox, M., & Coates, J. (2012). Influencing Controlled Substance Prescribing: Attending and Resident Physician Use of a State Prescription Monitoring Program. *Pain Medicine, 13*(7), 908–914.
<https://doi.org/10.1111/j.1526-4637.2012.01412.x>

Field, A. (2013). *Discovering Statistics using IBM SPSS Statistics*. Sage. Retrieved from [https://books.google.com/books?hl=en&lr=&id=c0Wk9IuBmAoC&oi=fnd&pg=P2&dq=discovering+statistics+using+ibm+spss&ots=LbBnLM3u5D&sig=uRLvAGfdnpawZrGkqotYeYL5A3s#v=onepage&q=discovering statistics using ibm spss&f=false](https://books.google.com/books?hl=en&lr=&id=c0Wk9IuBmAoC&oi=fnd&pg=P2&dq=discovering+statistics+using+ibm+spss&ots=LbBnLM3u5D&sig=uRLvAGfdnpawZrGkqotYeYL5A3s#v=onepage&q=discovering+statistics+using+ibm+spss&f=false)

Florence, C., Luo, F., Xu, L., & Zhou, C. (2016). The Economic Burden of Prescription Opioid Overdose, Abuse and Dependence in the United States. *Medical Care*.
<https://doi.org/10.1097/MLR.0000000000000625>

Ganem, V. J., Mora, A. G., Varney, S. M., & Bebart, V. S. (2014). Emergency Department Opioid Prescribing Practices for Chronic Pain: a 3-Year Analysis.
<https://doi.org/10.1007/s13181-014-0449-5>

Gebauer, S., Salas, J., & Scherrer, J. F. (2017). Neighborhood Socioeconomic Status and Receipt of Opioid Medication for New Back Pain Diagnosis. *Journal of the American Board of Family Medicine : JABFM, 30*(6), 775–783.
<https://doi.org/10.3122/jabfm.2017.06.170061>

- Germossa, G. N. (2018). *History Pain and Pain Management*. Retrieved from <http://crimsonpublishers.com/rmes/pdf/RMES.000567.pdf>
- Gugelmann, H., Shofer, F. S., Meisel, Z. F., & Perrone, J. (2013). Multidisciplinary intervention decreases the use of opioid medication discharge packs from 2 urban EDs. <https://doi.org/10.1016/j.ajem.2013.06.002>
- Hall, W., & Strang, J. (2017). Value for money in reducing opioid-related deaths. *Www.TheLancet.Com/Public-Health*, 2. [https://doi.org/10.1016/S2468-2667\(17\)30027-0](https://doi.org/10.1016/S2468-2667(17)30027-0)
- Han, B., Compton, W. M., Blanco, C., Crane, E., Lee, J., & Jones, C. M. (2014). Prescription Opioid Use, Misuse, and Use Disorders in U.S. Adults: 2015 National Survey on Drug Use and Health. *Annals of Internal Medicine*. <https://doi.org/10.7326/M17-0865>
- Han, B., Compton, W. M., Blanco, C., Crane, E., Lee, J., & Jones, C. M. (2017). Prescription Opioid Use, Misuse, and Use Disorders in U.S. Adults: 2015 National Survey on Drug Use and Health. *Annals of Internal Medicine*, 167(5), 293. <https://doi.org/10.7326/M17-0865>
- Hari, R., Henriksson, L., Malinen, S., & Parkkonen, L. (2015). Centrality of Social Interaction in Human Brain Function. *Neuron*, 88(1), 181–193. <https://doi.org/10.1016/j.neuron.2015.09.022>
- Hollingshead, N. A. (2016). Healthcare providers' perceptions of socioeconomically disadvantaged patients with chronic pain: A qualitative investigation. *Journal of Health Disparities Research and Practice*, 9(3), 35–44.

- Hoppe, J. A., Kim, H., & Heard, K. (2014). Association of Emergency Department Opioid Initiation with Recurrent Opioid Use. *Annals of Emergency Medicine*, 65(5), 493–499. <https://doi.org/10.1016/j.annemergmed.2014.11.015>
- Hoppe, J. A., Mcstay, C., Sun, B. C., Capp, R., & Hess, J. (2017). Emergency Department Attending Physician Variation in Opioid Prescribing in Low Acuity Back Pain. *Western Journal of Emergency Medicine*, 18(6). <https://doi.org/10.5811/westjem.2017.7.33306>
- Hoppe, J. A., Nelson, L. S., Perrone, J., Weiner, S. G., Niels, K., Sanchez, L. D., ... Koploy, A. (2015). Opioid Prescribing in a Cross Section of US Emergency Departments. *Annals of Emergency Medicine*, 66(3), 253-259.e1. <https://doi.org/10.1016/j.annemergmed.2015.03.026>
- Hsiao, C.-J. (2010). *Understanding and Using NAMCS and NHAMCS Data Data Tools and Basic Programming Techniques*. Retrieved from https://www.cdc.gov/nchs/ppt/nchs2010/03_Hsiao.pdf
- Hudley, C., Durvasula, R., Jones, D., Pietrantonio, K., Malon, R. R., & Ruiz, J. (2014). *Examining the Complexities between Health Disparities and Poverty* APA Office on Socioeconomic Status. Retrieved from <http://www.apa.org/pi/ses/resources/poverty-bibliography.aspx>.
- Hughes, A., Williams, M. R., Lipari, R. N., Bose, J., International, R., Copello, E. A. P., & Kroutil, L. A. (2016). Prescription Drug Use and Misuse in the United States: Results from the 2015 National Survey on Drug Use and Health. *National Survey on Drug Use and Health*. Retrieved from

<https://www.samhsa.gov/data/sites/default/files/NSDUH-FFR2-2015/NSDUH-FFR2-2015.pdf>

Hui Chen, L., Hedegaard, H., & Warner, M. (2014). Drug-poisoning Deaths Involving Opioid Analgesics: United States, 1999-2011 Key findings. *CDC: NCHS Data Brief*. Retrieved from <http://www.cdc.gov/nchs/>

International Narcotics Control Board. (2006). *International Narcotics Control Board Abuse of Prescription Drugs to Surpass Illicit Drug Abuse, Says Incb*. Retrieved from www.unis.unvienna.org

Jeffery, M. M., Hooten, W. M., Hess, E. P., Meara, E. R., Ross, J. S., Henk, H. J., ... Bellolio, M. F. (2018). Opioid Prescribing for Opioid-Naive Patients in Emergency Departments and Other Settings: Characteristics of Prescriptions and Association With Long-Term Use. *Annals of Emergency Medicine*, 71(3), 326-336.e19. <https://doi.org/10.1016/j.annemergmed.2017.08.042>

Joglekar, S. (2015). Logistic Regression (for dummies) | Sachin Joglekar's blog. Retrieved April 13, 2018, from <https://codesachin.wordpress.com/2015/08/16/logistic-regression-for-dummies/>

Joynt, M., Train, M. K., Robbins, B. W., Halterman, J. S., Caiola, E., & Fortuna, R. J. (2013). The Impact of Neighborhood Socioeconomic Status and Race on the Prescribing of Opioids in Emergency Departments Throughout the United States. *J Gen Intern Med*, 28(12), 1604–1614. <https://doi.org/10.1007/s11606-013-2516-z>

Juurlink, D. N., & Dhalla, I. A. (2012). Dependence and Addiction During Chronic

Opioid Therapy. <https://doi.org/10.1007/s13181-012-0269-4>

Kata, V., Novitch, M. B., Jones, M. R., Anyama, B. O., Helander, E. M., & Kaye, A. D.

(2018). Opioid addiction, diversion, and abuse in chronic and cancer pain.

Current Opinion in Supportive and Palliative Care, 12(2), 124–130.

<https://doi.org/10.1097/SPC.0000000000000333>

Kea, B., Fu, R., Lowe, R. A., & Sun, B. C. (2016a). Interpreting the National Hospital

Ambulatory Medical Care Survey: United States Emergency Department Opioid

Prescribing, 2006-2010. *Academic Emergency Medicine : Official Journal of the*

Society for Academic Emergency Medicine, 23(2), 159–165.

<https://doi.org/10.1111/acem.12862>

Kea, B., Fu, R., Lowe, R. A., & Sun, B. C. (2016b). Interpreting the National Hospital

Ambulatory Medical Care Survey: United States Emergency Department Opioid

Prescribing, 2006-2010. In *Academic Emergency Medicine*.

<https://doi.org/10.1111/acem.12862>

Kilaru, A. S., Gadsden, S. M., Perrone, J., Paciotti, B., Barg, F. K., & Meisel, Z. F.

(2014). How Do Physicians Adopt and Apply Opioid Prescription Guidelines in

the Emergency Department? A Qualitative Study. *Annals of Emergency Medicine*,

64, 482-489.e1. <https://doi.org/10.1016/j.annemergmed.2014.03.015>

Kim, H.-Y. (2017). Statistical notes for clinical researchers: Chi-squared test and Fisher's

exact test. *Restorative Dentistry & Endodontics*, 42(2), 152–155.

<https://doi.org/10.5395/rde.2017.42.2.152>

King, N. B., Fraser, V., Boikos, C., Richardson, R., & Harper, S. (2014). Determinants of

Increased Opioid-Related Mortality in the United States and Canada, 1990–2013: A Systematic Review. *Am J Public Health*, 104, 32–42.

<https://doi.org/10.2105/AJPH.2014.301966>

Knopf, T. (2017, June 19). How Race and Class Drive Factors of the Opioid Crisis & Legislation - North Carolina Health News. *North Carolina Health News*. Retrieved from <https://www.northcarolinahealthnews.org/2017/06/19/how-race-and-class-drive-factors-of-the-opioid-crisis-legislation/>

Lani, J. (2015). Assumptions of Logistic Regression. *Statistics Solutions*. Retrieved from <http://www.statisticssolutions.com>

Lembke, A. (2016). *Drug Dealer, MD*. Boston, MA: John Hopkins University Press. Retrieved from <https://jhupbooks.press.jhu.edu/content/drug-dealer-md>

Maly, A., & Vallerand, A. H. (2018). *Neighborhood, Socioeconomic, and Racial Influence on Chronic Pain*. <https://doi.org/10.1016/j.pmn.2017.11.004>

Manchikanti, L., Giordano, J., Boswell, M. V, Fellows, B., Manchukonda, R., & Pampati, V. (2007). Psychological factors as predictors of opioid abuse and illicit drug use in chronic pain patients. *Journal of Opioid Management*, 3(2), 89–100. Retrieved from <http://www.ncbi.nlm.nih.gov/pubmed/17520988>

Manchikanti, L., Helm II, S., Fellows, B., Janata, J., Pampati, V., Grider, J., & Boswell, M. V. (2012). Opioid Epidemic in the United States. *Pain Physician*, 15.

Maycock, B. (2015). Understanding the Public's Health Problems. *Asia Pacific Journal of Public Health*, 27(1), 24–28. <https://doi.org/10.1177/1010539514561086>

Mazer-Amirshahi, M., Mullins, P. M., Rasooly, I., Van Den Anker, J., & Pines, J. M.

(2014). Rising opioid prescribing in adult U.S. emergency department visits:

2001-2010. *Academic Emergency Medicine*, 21(3), 236–243.

<https://doi.org/10.1111/acem.12328>

Mazer-Amirshahi, M., Mullins, P. M., Sun, C., Pines, J. M., Nelson, L. S., & Perrone, J.

(2016). Trends in Opioid Analgesic Use in Encounters Involving Physician

Trainees in U.S. Emergency Departments. *Pain Medicine*, 17(12), 2389–2396.

<https://doi.org/10.1093/pm/pnw048>

McCaig, L. F., & McLemore, T. (1994). *Vital and Health Statistics ~ Plan and Operation*

of the National Hospital Ambulatory Medical Survey. Retrieved from

https://www.cdc.gov/nchs/data/series/sr_01/sr01_034acc.pdf

Mcdonald, D. C., Carlson, K., & Izrael, D. (2012). Geographic Variation in Opioid

Prescribing in the U.S. *J Pain*, 13(10), 988–996.

<https://doi.org/10.1016/j.jpain.2012.07.007>

Meldrum, M. L. (2003). A Capsule History of Pain Management. *JAMA*, 290. Retrieved

from

http://www.mccklik.nl/system/ckeditor_assets/attachments/455/Capsule_history_pain_management_JAMA_2003.pdf

Methadone | CESAR. (n.d.). Retrieved August 10, 2018, from

<http://www.cesar.umd.edu/cesar/drugs/methadone.asp>

Meyer, R., Patel, A. M., Rattana, S. K., Quock, T. P., & Mody, S. H. (2014). Prescription

Opioid Abuse: A Literature Review of the Clinical and Economic Burden in the

United States. *Population Health Management*, 17, 372–387.

<https://doi.org/10.1089/pop.2013.0098>

- Michael, S. S., Babu, K. M., Androski, C., & Reznick, M. A. (2018). Effect of a Data-driven Intervention on Opioid Prescribing Intensity Among Emergency Department Providers: A Randomized Controlled Trial. *Academic Emergency Medicine*, 25(5), 482–493. <https://doi.org/10.1111/acem.13400>
- Mills, S., Torrance, N., & Smith, B. H. (2016). Identification and Management of Chronic Pain in Primary Care: a Review. *Current Psychiatry Reports*, 18(2), 22. <https://doi.org/10.1007/s11920-015-0659-9>
- Morone, N. E., & Weiner, D. K. (2013). Pain as the 5th Vital Sign: Exposing the Vital Need for Pain Education Introduction of Pain as the 5th Vital Sign and Clinician. *Clin Ther*, 35(11), 1728–1732. <https://doi.org/10.1016/j.clinthera.2013.10.001>
- Muhuri, P. K., Gfroerer, J. C., & Davies, M. C. (2013). *CBHSQ Data Review: Associations of Nonmedical Pain Reliever Use and Initiation of Heroin Use in the United States*. Retrieved from <http://www.samhsa.gov/data/>.
- Murthy, V. H. (2016). Ending the Opioid Epidemic - A Call to Action. *New England Journal of Medicine*, 37525. Retrieved from <https://www.nejm.org/doi/pdf/10.1056/NEJMp1612578>
- Nahin, R. L. (2015). Estimates of Pain Prevalence and Severity in Adults: United States, 2012. *Journal of Pain*, 16. <https://doi.org/10.1016/j.jpain.2015.05.002>
- National Academies of Sciences, Engineering, and Medicine. (2017). *Pain management and the opioid epidemic: Balancing societal and individual benefits and risks of prescription opioid use*. Washington, DC: The National Academies Press.

doi:<https://doi.org/10.17226/24781>

- National Center for Health Statistics. (2015a). 2015 National Ambulatory Medical Care Survey Public Use Micro-Data File Documentation. *Healthdata.Gov*. Retrieved from https://ftp.cdc.gov/pub/health_statistics/nchs/dataset_documentation/NAMCS/doc2015.pdf
- National Center for Health Statistics. (2015b). 2015 National Hospital Ambulatory Medical Care Survey Emergency Department Public Use Data File Documentation, 1–156. Retrieved from <http://www.nber.org/nhamcs/docs/nhamcsed2015.pdf>
- National Center for Health Statistics. (2015c). National Electronic Health Records Survey 2015. Retrieved from https://www.cdc.gov/nchs/data/ahcd/2015_NEHRS.pdf
- National Center for Health Statistics. (2015d). NHAMCS-174 SAMPLE NATIONAL HOSPITAL AMBULATORY MEDICAL CARE SURVEY 2015 OUTPATIENT DEPARTMENT PATIENT RECORD. Retrieved September 18, 2018, from https://www.cdc.gov/nchs/data/ahcd/2015_NHAMCS_OPD_PRF_Sample.pdf
- National Center for Health Statistics. (2017). *National Hospital Ambulatory Medical Care Survey: 2015 Emergency Department Summary Tables*. Retrieved from http://www.cdc.gov/nchs/ahcd/ahcd_survey_instruments.htm#nhamcs.
- Neven, D. E., Sabel, J. C., Howell, D. N., & Carlisle, R. J. (2012). The Development of the Washington State Emergency Department Opioid Prescribing Guidelines. *Journal of Medic*. <https://doi.org/10.1007/s13181-012-0267-6>

- Notenboom, H. (2017). *Oregon ACEP Opioid Prescribing Guidelines*. Retrieved from [https://www.oahhs.org/assets/documents/files/R3 Notenboom, Hans - Opioid Prescribing.pdf](https://www.oahhs.org/assets/documents/files/R3_Notenboom_Hans_-_Opioid_Prescribing.pdf)
- Noyes, J. (2017). Use of sociological theories and models in research. *Journal of Advanced Nursing*, 73(7), 1538–1538. <https://doi.org/10.1111/jan.13014>
- Olson, K. (2013). History of Pain: A Brief Overview of the 19th and 20th Centuries. *Practical Pain Management*, 13. Retrieved from <https://www.practicalpainmanagement.com/treatments/history-pain-brief-overview-19th-20th-centuries>
- Opioids and methamphetamine: a tale of two crises. (2018). *Lancet*, 391. [https://doi.org/10.1016/S0140-6736\(18\)30319-2](https://doi.org/10.1016/S0140-6736(18)30319-2)
- Paparella, S. F. (2014). Intravenous fentanyl: understanding and managing the risk. *Journal of Emergency Nursing: JEN : Official Publication of the Emergency Department Nurses Association*, 40(5), 488–490. <https://doi.org/10.1016/j.jen.2014.05.017>
- Patel, N. A., & Afshar, S. (2017). Addressing the high rate of opioid prescriptions for dental pain in the emergency department. *American Journal of Emergency Medicine*, 36, 138–139. <https://doi.org/10.1016/j.ajem.2017.07.003>
- Patulny, R., Siminski, P., & Mendolia, S. (2015). The front line of social capital creation – A natural experiment in symbolic interaction. *Social Science & Medicine*, 125, 8–18. <https://doi.org/10.1016/J.SOCSCIMED.2014.04.026>
- Perrone, J., DeRoos, F. J., & Nelson, L. S. (2012). Prescribing Practices, Knowledge, and

Use of Prescription Drug Monitoring Programs (PDMP) by a National Sample of Medical Toxicologists, 2012. *Journal of Medical Toxicology*, 8(4), 341–352.

<https://doi.org/10.1007/s13181-012-0250-2>

Pert, C. B., & Snyder, S. H. (1976). Correlation of opiate receptor affinity with analgetic effects of meperidine homologues. *Journal of Medicinal Chemistry*, 19(10), 1248–1250. Retrieved from <http://www.ncbi.nlm.nih.gov/pubmed/11345>

Pletcher, M. J., Kertesz, S. G., Kohn, M. A., & Gonzales, R. (2008). Trends in Opioid Prescribing by Race/Ethnicity for Patients Seeking Care in US Emergency Departments. *JAMA*, 299(1), 70–78. <https://doi.org/10.1001/jama.2007.64>

Pomerleau, A. C., Schrage, J. D., & Morgan, B. W. (2016). Pilot Study of the Importance of Factors Affecting Emergency Department Opioid Analgesic Prescribing Decisions. *Journal of Medical Toxicology*, 12.

<https://doi.org/10.1007/s13181-016-0553-9>

Poon, S. J., & Greenwood-Ericksen, M. B. (2014). The opioid prescription epidemic and the role of emergency medicine. *Annals of Emergency Medicine*, 64(5), 490–495.

<https://doi.org/10.1016/j.annemergmed.2014.06.016>

Porucznik, C. A., Johnson, E. M., Rolfs, R. T., Sauer, B. C., & Porucznik, C. (2014).

OPIOIDS, SUBSTANCE ABUSE & ADDICTIONS SECTION Specialty of Prescribers Associated with Prescription Opioid Fatalities in Utah, 2002–2010.

Pain Medicine. Retrieved from [https://watermark.silverchair.com/15-1-](https://watermark.silverchair.com/15-1-73.pdf?token=AQECAHi208BE49Ooan9kKhW_Ercy7Dm3ZL_9Cf3qfKAc485ysgAAa4wggGqBgkqhkiG9w0BBwaggGbmIIB1wIBADCCAZAGCSqGSIB3D)

[73.pdf?token=AQECAHi208BE49Ooan9kKhW_Ercy7Dm3ZL_9Cf3qfKAc485ysgAAa4wggGqBgkqhkiG9w0BBwaggGbmIIB1wIBADCCAZAGCSqGSIB3D](https://watermark.silverchair.com/15-1-73.pdf?token=AQECAHi208BE49Ooan9kKhW_Ercy7Dm3ZL_9Cf3qfKAc485ysgAAa4wggGqBgkqhkiG9w0BBwaggGbmIIB1wIBADCCAZAGCSqGSIB3D)

QEHATAeBglghkgBZQMEAS4wEQQMruAHFh78fdNAfZ2DAgEQgIIBYT6c4
xMG5743-4yAX45p2-VjuQ0ozDK8UOFa7o0I7kuqJmH

Prunuske, J. P., St. Hill, C. A., Hager, K. D., Lemieux, A. M., Swanoski, M. T.,

Anderson, G. W., & Lutfiyya, M. N. (2014). Opioid prescribing patterns for non-malignant chronic pain for rural versus non-rural US adults: a population-based study using 2010 NAMCS data. *BMC Health Services Research*, *14*(1), 563.

<https://doi.org/10.1186/s12913-014-0563-8>

Redmond, M. V. (2015). Symbolic Interactionism. *English Technical Reports and White Papers.*, 4. Retrieved from http://lib.dr.iastate.edu/engl_reports

Reis-Pina, P., Lawlor, P. G., & Barbosa, A. (2015). *Cancer-Related Pain Management and the Optimal Use of Opioids*. *Cancer-Related Pain Management and the Optimal Use of Opioids* (Vol. 28). Retrieved from

<https://www.actamedicaportuguesa.com/revista/index.php/amp/article/view/5801/4355>

Ringwalt, C., Roberts, A. W., Gugelmann, H., Cockrell Skinner, A., & Author, C. (2015).

Racial disparities across provider specialties in opioid prescriptions dispensed to Medicaid beneficiaries with chronic non-cancer pain HHS Public Access. *Pain Med*, *16*(4), 633–640. <https://doi.org/10.1111/pme.12555>

Roe, J., Joseph, S., & Middleton, H. (2010). Symbolic interaction: a theoretical approach to understanding stigma and recovery. *Mental Health Review Journal*, *15*.

<https://doi.org/10.5042/mhrj.2010.0200>

Rogers, S. O. (2018). Addressing Variability in Opioid Prescribing. *JAMA Surgery*,

153(1), 43. <https://doi.org/10.1001/jamasurg.2017.3166>

Rudd, R. A., Aleshire, N., Zibbell, J. E., & Gladden, R. M. (2016). Increases in Drug and Opioid Overdose Deaths — United States, 2000–2014. Retrieved August 8, 2018, from <https://www.cdc.gov/mmwr/preview/mmwrhtml/mm6450a3.htm>

Rudd, R. A., Seth, P., David, F., & Scholl, L. (2016). Increases in Drug and Opioid-Involved Overdose Deaths — United States, 2010–2015. *MMWR. Morbidity and Mortality Weekly Report*, 65(5051), 1445–1452. <https://doi.org/10.15585/mmwr.mm655051e1>

Sabatowski, R., Schafer, D., Kasper, S., Brunsch, H., & Radbruch, L. (2004). Pain Treatment: A Historical Overview. *Current Pharmaceutical Design*, 10(7), 701–716. <https://doi.org/10.2174/1381612043452974>

Sasson, C., Smith, J., Kessler, C., Haukoos, J., Himstreet, J., Christopher, M., & Emmendorfer, T. (2018). Variability in opioid prescribing in veterans affairs emergency departments and urgent cares. *The American Journal of Emergency Medicine*, 0(0). <https://doi.org/10.1016/j.ajem.2018.08.044>

Sedeno, A. (2015). Pain as the 5 th vital sign. Retrieved from https://c.ymcdn.com/sites/www.fshp.org/resource/resmgr/se_2015_am/pain_as_the_5th_vital_sign.pdf

Sehgal, N., Manchikanti, L., & Smith, H. S. (2012). Prescription Opioid Abuse in Chronic Pain: A Review of Opioid Abuse Predictors and Strategies to Curb Opioid Abuse. *Narrative Review*, 15, 67–92. Retrieved from www.painphysicianjournal.com

- Seth, P. (2017). Quantifying the Epidemic of Prescription Opioid Overdose Deaths. *AJPH Surveillance*, 108. <https://doi.org/10.2105/AJPH.2017.304265>
- Seth, P., Scholl, L., Rudd, R. A., & Bacon, S. (2018). Overdose deaths involving opioids, cocaine, and psychostimulants - United States, 2015-2016. *American Journal of Transplantation*, 18(6), 1556–1568. <https://doi.org/10.1111/ajt.14905>
- Seth, P., Rudd, R. A., Noonan, R. K., & Haegerich, T. M. (2018). Quantifying the Epidemic of Prescription Opioid Overdose Deaths. *AJPH Surveillance*, 108. <https://doi.org/10.2105/AJPH.2017.304265>
- Seth, P., Scholl, L., Rudd, R. A., & Bacon, S. (2018). Overdose Deaths Involving Opioids, Cocaine, and Psychostimulants — United States, 2015–2016. *MMWR. Morbidity and Mortality Weekly Report*, 67(12), 349–358. <https://doi.org/10.15585/mmwr.mm6712a1>
- Shah, A. A., Zogg, C. K., Nabeel Zafar, S., Schneider, E. B., Cooper, L. A., Chapital, A. B., ... Haider, A. H. (2015). *Analgesic Access for Acute Abdominal Pain in the Emergency Department Among Racial/Ethnic Minority Patients A Nationwide Examination*. Retrieved from www.lww-medicalcare.com
- Sheldon, G. H. (2011). *Draft Blueprint for Prescriber Education for Long-Acting/Extended-Release Opioid Class-Wide Risk Evaluation and Mitigation Strategy; Availability; Request for Comments*. DEPARTMENT OF HEALTH AND HUMAN SERVICES Food and Drug Administration *Federal Register* (Vol. 76). Retrieved from <http://www.fda.gov/Drugs/DrugSafety/InformationbyDrugClass/ucm163654.htm>.

- Singhal, A., Tien, Y. Y., & Hsia, R. Y. (2016). Racial-ethnic disparities in opioid prescriptions at emergency department visits for conditions commonly associated with prescription drug abuse. *PLoS ONE*, *11*(8), 1–14.
<https://doi.org/10.1371/journal.pone.0159224>
- Sinnenberg, L. E., Wanner, K. J., Perrone, J., Barg, F. K., Rhodes, K. V., & Meisel, Z. F. (2017). What Factors Affect Physicians' Decisions to Prescribe Opioids in Emergency Departments? *MDM Policy* (2).
<https://doi.org/10.1177/2381468316681006>
- Sites, B. D., Beach, M. L., & Davis, M. (2014). Increases in the Use of Prescription Opioid Analgesics and the Lack of Improvement in Disability Metrics among Users. *Reg Anesth Pain Med*. <https://doi.org/10.1097/AAP.0000000000000022>
- Smulowitz, P. B., Chris Cary, B., Katherine Boyle, B. L., & Jagminas, L. (2016). Variation in opioid prescribing patterns between ED providers. *Internal Emergency Medicine*, *11*. <https://doi.org/10.1007/s11739-016-1505-8>
- Sperandei, S. (2014). Understanding logistic regression analysis Lessons in biostatistics. *Biochemia Medica*, *24*(1), 12–18. <https://doi.org/10.11613/BM.2014.003>
- Stanley, T. H. (2014). The fentanyl story. *The Journal of Pain : Official Journal of the American Pain Society*, *15*(12), 1215–1226.
<https://doi.org/10.1016/j.jpain.2014.08.010>
- Stoltzfus, J. C. (2011). Logistic Regression: A Brief Primer. *ACADEMIC EMERGENCY MEDICINE*, *18*, 1099–1104. <https://doi.org/10.1111/j.1553-2712.2011.01185.x>
- Substance Abuse and Mental Health Services Administration. (2016). Results from the

2015 National Survey on Drug Use and Health: Detailed Tables Prevalence Estimates, Standard Errors, P Values, and Sample Sizes. *Center for Behavioral Health Statistics*. Retrieved from <https://www.samhsa.gov/data/sites/default/files/NSDUH-DetTabs-2015/NSDUH-DetTabs-2015/NSDUH-DetTabs-2015.pdf>

Sullivan, L. M. (n.d.). Confidence Intervals. Retrieved May 17, 2018, from http://sphweb.bumc.bu.edu/otlt/MPH-Modules/BS/BS704_Confidence_Intervals/BS704_Confidence_Intervals_print.html

Tamayo-Sarver, J. H., Dawson, N. V., Hinze, S. W., Cydulka, R. K., Wigton, R. S., Albert, J. M., ... Baker, D. W. (2003). The Effect of Race/Ethnicity and Desirable Social Characteristics on Physicians' Decisions to Prescribe Opioid Analgesics. *Academic Emergency Medicine*, *10*(11), 1239–1248. [https://doi.org/10.1197/S1069-6563\(03\)00494-9](https://doi.org/10.1197/S1069-6563(03)00494-9)

Tamayo-Sarver, J. H., Dawson, N. V., Cydulka, R. K., Wigton, R. S., & Baker, D. W. (2004). Variability in emergency physician decisionmaking about prescribing opioid analgesics. *Annals of Emergency Medicine*, *43*(4), 483–493. <https://doi.org/10.1016/j.annemergmed.2003.10.043>

Tompkins, D. A., Hobelmann, J. G., & Compton, P. (2017). Providing chronic pain management in the “Fifth Vital Sign” Era: Historical and treatment perspectives on a modern-day medical dilemma. *Drug and Alcohol Dependence*, *173*, S11–S21. <https://doi.org/10.1016/j.drugalcdep.2016.12.002>

- U.S. Department of Health and Human Services. (2013). *Drug Abuse Warning Network, 2011: National Estimates of Drug-Related Emergency Department Visits*. Retrieved from <http://store.samhsa.gov/orpleasecall>
- Vivolo-Kantor, A. M., Seth, P., Gladden, R. M., Mattson, C. L., Grant, T. G., Baldwin, G. T., ... Coletta, M. A. (2016). Morbidity and Mortality Weekly Report Vital Signs: Trends in Emergency Department Visits for Suspected Opioid Overdoses-United States. *Morbidity and Mortality Report*. Retrieved from <https://surveillance.cancer.gov/joinpoint/>.
- Vivolo-Kantor, A. M., Seth, P., Gladden, R. M., Mattson, C. L., Baldwin, G. T., Kite-Powell, A., & Coletta, M. A. (2018). Vital Signs: Trends in Emergency Department Visits for Suspected Opioid Overdoses — United States, July 2016–September 2017. *MMWR. Morbidity and Mortality Weekly Report*, 67(9), 279–285. <https://doi.org/10.15585/mmwr.mm6709e1>
- Von Korff, M., Scher, A. I., Helmick, C., Carter-Pokras, O., Dodick, D. W., Goulet, J., Mackey, S. (2016). United States National Pain Strategy for Population Research: Concepts, Definitions, and Pilot Data. *The Journal of Pain : Official Journal of the American Pain Society*, 17(10), 1068–1080. <https://doi.org/10.1016/j.jpain.2016.06.009>
- Vowles, K. E. (2015). Rates of Opioid Misuse, Abuse, and Addiction in Chronic Pain. *PAIN*. Retrieved from <https://30qkon2g8eif8wrj03zeh041-wpengine.netdna-ssl.com/wp-content/uploads/2017/12/PCSS-O-Vowles-Opioid-Use-04-11-2017.pdf>

- Weiner, S. G., Griggs, C. A., Mitchell, P. M., Langlois, B. K., Friedman, F. D., Moore, R. L., ... Feldman, J. A. (2013). Clinician Impression Versus Prescription Drug Monitoring Program Criteria in the Assessment of Drug-Seeking Behavior in the Emergency Department. *Annals of Emergency Medicine*, 62(4), 281–289.
<https://doi.org/10.1016/J.ANNEMERGMED.2013.05.025>
- Weiss, A. J., Wier, L. M., Stocks, C., & Blanchard, J. (2014). Overview of Emergency Department Visits in the United States, 2011. *Agency for Healthcare Research and Quality*. Retrieved from <https://www.hcup-us.ahrq.gov/reports/statbriefs/sb174-Emergency-Department-Visits-Overview.pdf>
- West, R. L., & Turner, L. H. (2018). *Introducing communication theory : analysis and application* (Sixth edit). New York: McGraw-Hill Education. Retrieved from <https://www.worldcat.org/title/introducing-communication-theory-analysis-and-application/oclc/967775008>
- Yacisin, K., O'Connor, K., & Akinseye, A. (2018). QuickStats: Percentage of Emergency Department Visits That Had an Opioid* Ordered or Prescribed, by Age Group — National Hospital Ambulatory Medical Care Survey, United States, 2006–2015. *MMWR. Morbidity and Mortality Weekly Report*, 67(11), 344.
<https://doi.org/10.15585/mmwr.mm6711a8>
- Yang, B. K., Storr, C. L., Trinkoff, A. M., Sohn, M., Idzik, S. K., & McKinnon, M. (2018). National opioid prescribing trends in emergency departments by provider type: 2005–2015. *The American Journal of Emergency Medicine*.
<https://doi.org/10.1016/J.AJEM.2018.10.041>

Yasaei, R., & Saadabadi, A. (2018). *Meperidine*. *StatPearls*. StatPearls Publishing.

Retrieved from <http://www.ncbi.nlm.nih.gov/pubmed/29261967>

Appendix A: Patient Record Form

The first page of the form used to collect patient information (National Center for Health Statistics, 2015c).

SAMPLE
NATIONAL HOSPITAL AMBULATORY MEDICAL CARE SURVEY
2015 EMERGENCY DEPARTMENT PATIENT RECORD

NOTE: Public reporting burden for this collection of information is estimated to average 15 minutes per response, including the time for reviewing instructions, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. An agency may not conduct or sponsor a collection of information unless it displays a currently valid OMB control number. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing the burden, to Washington Headquarters Service, Paperwork Project, (0158-0047), Washington, DC 20503-2907.

WARNING: All information furnished on this form is for the use of the Department of Health and Human Services, and its contractors, only. It is not to be disclosed outside of the Department of Health and Human Services, and its contractors, without the express written approval of the Privacy Officer, Office of Management and Enterprise Services, Department of Health and Human Services, 2025 E. Duane Street, Rockville, MD 20850.

PATIENT INFORMATION

Name (last, first, middle) _____ Date of birth (MM/DD/YYYY) _____
 Sex _____ Race _____ Ethnicity _____
 Patient residence _____
 Patient insurance _____
 Date and time of admission (MM/DD/YYYY) _____
 Date and time of discharge (MM/DD/YYYY) _____
 Date and time of ED departure (MM/DD/YYYY) _____
 Arrival by ambulance _____
 Discharge status _____
 Discharge location _____

REASON FOR VISIT

Chief complaint _____
 Reason for visit _____
 Reason for visit _____
 Reason for visit _____
 Reason for visit _____

ADMISSION

Admission type _____
 Admitted to _____
 Discharge status _____
 Discharge location _____

DIAGNOSIS

Primary diagnosis _____
 Secondary diagnosis _____
 Tertiary diagnosis _____
 Quaternary diagnosis _____
 Quinary diagnosis _____

PROCEDURES

Procedure _____
 Procedure _____
 Procedure _____
 Procedure _____
 Procedure _____

Appendix B: Hospital Induction Form

The first page of the hospital induction form (National Center for Health Statistics, 2015d).

<p>National Electronic Health Records Survey OMB No. 0920-1015: Approval expires 04/30/2017</p>	
<p>NOTICE - Public reporting burden of this collection of information is estimated to average 30 minutes per response, including the time for reviewing instructions, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. An agency may not conduct or sponsor, and a person is not required to respond to, a collection of information unless it displays a currently valid OMB control number. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden to: CDC/ATSDR Information Collection Review Office, 1600 Clifton Road, MS D-74, Atlanta, GA 30333, ATTN: PRA (0920-1015).</p> <p>Assurance of Confidentiality - All information which would permit identification of an individual, a practice, or an establishment will be held confidential, will be used only by NCHS staff, contractors, and agents only when required and with necessary controls, and will not be disclosed or released to other persons without the consent of the individual or the establishment in accordance with section 308(d) of the Public Health Service Act (42 USC 242m) and the Confidential Information Protection and Statistical Efficiency Act (PL-107-347).</p>	
<h2>National Electronic Health Records Survey 2015</h2> <p>The National Electronic Health Records Survey is affiliated with the National Ambulatory Medical Care Survey (NAMCS). The purpose of the survey is to collect information about the adoption of electronic health records/electronic medical records (EHRs/EMRs) in ambulatory care settings. Your participation is greatly appreciated. Your answers are completely confidential. Participation in this survey is voluntary. If you have questions or comments about this survey, please call 866-966-1473.</p>	
<p>1. We have your specialty as:</p> <p>Is that correct?</p> <p><input type="checkbox"/> 1 Yes</p> <p><input type="checkbox"/> 2 No → What is your specialty? _____</p> <p style="font-size: x-small; text-align: center;">This survey asks about ambulatory care, that is, care for patients receiving health services without admission to a hospital or other facility.</p> <p>2. Do you directly care for any ambulatory patients in your work?</p> <p><input type="checkbox"/> 1 Yes → Continue to Question 3</p> <p><input type="checkbox"/> 2 No</p> <p><input type="checkbox"/> 3 I am no longer in practice</p> <p style="font-size: x-small; text-align: center;">Please stop here and return the questionnaire in the envelope provided. Thank you for your time.</p> <p style="font-size: x-small; text-align: center;">The next question asks about a normal week. We define a normal week as a week with a normal caseload, with no holidays, vacations, or conferences.</p> <p>3. Overall, at how many office locations (excluding hospital emergency or hospital outpatient departments) do you see ambulatory patients in a normal week?</p> <p>_____ Locations</p>	<p>4. Do you see ambulatory patients in any of the following settings? CHECK ALL THAT APPLY.</p> <p><input type="checkbox"/> 1 Private solo or group practice</p> <p><input type="checkbox"/> 2 Freestanding clinic/urgent care (not part of a hospital outpatient department)</p> <p><input type="checkbox"/> 3 Community Health Center (e.g., Federally Qualified Health Center (FQHC), federally funded clinics or "look-alike" clinics)</p> <p><input type="checkbox"/> 4 Mental health center</p> <p><input type="checkbox"/> 5 Non-federal government clinic (e.g., state, county, city, maternal and child health, etc.)</p> <p><input type="checkbox"/> 6 Family planning clinic (including Planned Parenthood)</p> <p><input type="checkbox"/> 7 Health maintenance organization or other prepaid practice (e.g., Kaiser Permanente)</p> <p><input type="checkbox"/> 8 Faculty practice plan (an organized group of physicians that treats patients referred to an academic medical center)</p> <p><input type="checkbox"/> 9 Hospital emergency or hospital outpatient departments</p> <p><input type="checkbox"/> 10 None of the above</p> <p style="font-size: x-small; text-align: right;">If you see patients in any of these settings, go to Question 5</p> <p style="font-size: x-small; text-align: right;">If you select only 9 or 10, go to Question 42</p>
<p>5. At which of the settings (1-8) in question 4 do you see the most ambulatory patients? WRITE THE NUMBER LOCATED NEXT TO THE BOX YOU CHECKED.</p> <p>_____ (For the rest of the survey, we will refer to this as the "reporting location.")</p> <p style="font-size: x-small; text-align: center;">For the remaining questions, please answer regarding the reporting location indicated in question 5 even if it is not the location where this survey was sent.</p>	
<p>6. What are the county, state, zip code, and telephone number of the reporting location?</p> <p>Country <u>USA</u> County _____ State _____</p> <p>Zip Code _____ Telephone (____) _____</p>	