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Health Insurance Coverage, Sociodemographic Factors, and Treatment Completion for Opioid Abusers in Indiana

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This is to certify that the doctoral dissertation by

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has been found to be complete and satisfactory in all respects,
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Walden University
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Abstract

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MPH, Indiana Wesleyan University, 2016

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Dissertation Submitted in Partial Fulfillment

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Abstract

Many accidental deaths have recently occurred in Indiana due to opioid overdose. The current study sought to assess the association between sociodemographic factors, health insurance, and successful treatment completion for opioids abusers in Indiana based on the existing literature gap. In this study, the dependent variables considered were treatment completion status and opioid abuse. The independent variables included health insurance coverage and sociodemographic factors of education, marital status, employment status, race, gender, and age. I measured both dependent and independent variables as categorical. A cross-sectional and quantitative research approach was used by analyzing data from the 2017-Treatment Episode Data Set Discharges (TEDS-D) using the Statistical Package for the Social Sciences (SPSS) version 25.0.Descriptive statistics, chi-square, bivariate, and multivariate logistic regression were applied to evaluate the association. Significant findings revealed that individuals in “not in labor force” were 2.0 times more likely [OR=2.042, 95% CI (1.853, 2.252), p<0.0001], unemployed were 1.8 times more likely [OR=1.785, 95% CI (1.662, 1.916), p<0.0001], and part-timers were 1.4 times more likely [OR=1.406, 95% (1.269, 1.557), p<0.0001] to complete treatment compared to full-time workers. The outcomes showed that compared to insured, uninsured individuals were less likely [OR=0.704, 95% CI (0.662, 0.749), p<0.0001] to complete treatment. Intervention plans such as increasing screening among vulnerable populations, mass education, and advocacy for health insurance coverage could promote positive social change by decreasing opioid-related mortality and improving treatment outcomes in Indiana.

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Dedication

This dissertation is dedicated to my wife, Hadizatou Samna, whose affection, support, and understanding throughout this journey have undoubtedly led to this current study's completion. This dissertation is further dedicated to my daughters, Aminatou, Farida, Zeinab, and Yasmina. To my mother, who witnessed the start of this dissertation and passed away a month after I started this study, I will carry this work as a testimony to make her prouder and keep her memory alive. Having both parents with primary education and being the only child in my family who make it to this education level have been the driving forces for me to reach this milestone. I knew from the beginning that the process would be challenging. However, I surrounded myself with the right people, which helped me overcome the obstacles.

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Chapter 1: Introduction to the Study

The World Drug Report of 2018 stated that opioid usage was at the highest level in recorded history and became is a major concern due to increased drug prescription misuse and the use of illegal opioids. The report found that prescription drug use has become a significant menace to public health and law enforcement agencies across the world. It showed that opioids cause the most harm with a mortality rate of 76 % where drug use disorders were involved (The United Nations Office on Drugs and Crime or [UNODC], 2018). Substance abuse, including alcohol, illicit drugs, and prescription drugs, persists and has become a significant health problem worldwide (Chakravarthy et al, 2013). Nearly 5% of the world's population used an illegal drug in 2010, and estimates revealed that 27 million individuals (0.6 % of world adult population) are considered problem drug users (Chakravarthy et al., 2013). Researchers have shown that alcohol alone claimed the lives of 2.5 million yearly while that heroin, cocaine, and other drugs were accounted for 0.1 to 0.2 million deaths each year. Substance abuse causes significant morbidity, while the treatment of drug addiction represents a real social burden (Chakravarthy et al., 2013). According to UNODC, the total costs for drug abuse treatment have been estimated to reach between $200-$250 billion, which constitutes about 0.3-0.4 % of world GDP (Chakravarthy et al., 2013). Researchers found that only 20% of drug users were admitted for treatment of drug dependency in 2010 (Chakravarthy et al., 2013). A report indicated that individuals who used drugs at least once a year in 2016 were aged 15-64 years old, accounting for 275 million people or(5.6% of the world population) [UNODC, 2018].

The use of addictive substances and the upsurge in drug abuse, along with its underlying health effects, have emerged as one of the prominent public health problems (Chaturvedi et al., 2009; Gomes et al., 2018). Additionally, over the past decades the use of medical and nonmedical prescription of opioids has become a growing concern in the United States (Bolshakova et al., 2018; Gomes et al., 2018; Lowder et al., 2018; McCabe et al., 2017; Meyer et al., 2014; Oderda et al., 2015; Wisniewski et al., 2008). However, researchers have indicated a marked decline in the use of medical and nonmedical opioids' prescription in recent years (Kolodny et al., 2015). The Centers for Disease Control and Prevention (CDC) stated that more than 190 million opioid-related prescriptions were supplied to American citizens in 2017 with wide variation among states. Despite government restrictions, the use of illicit drugs (e.g., heroin, cocaine) and other substances legally obtained (e.g., oxycodone, hydrocodone) has risen to an alarming level in the United States and particularly in Indiana. Because of the abuse, many thousands of people have overdosed and died. Additionally, statistics from the National Center for Health Statistics (NCHS) show that more than 70,000 people died in 2017 alone. It is estimated that an average of 130 United States citizens die every day because of opioid abuse (CDC, 2017). Furthermore, Gomes et al. (2018) noted the disability-adjusted life-years (DALYs) due to years of life lost (YLL) at over 800,000 for people under 65 years old in the United States as a result of opioid overdose. Opioid prescription abuse can lead to overdose, addiction, and substance abuse disorder (Han et al., 2017; McHugh et al., 2014; Morales et al., 2019).

In the state of Indiana,74, 000 people have abused opioids in 2017 (Brewer, 2018). About 1,700 Indiana residents died because of overdose (Richard Fairbanks Foundation, 2018). The populations most affected were individuals aged 25-34 years and 35-44years old, and males were more vulnerable than females (Gomes et al., 2018). According to the U.S Census Bureau (2018), Indiana State is home to 6,732,219 residents, with 51.86 % female and 48.14% male and racial groups are composed of 54.8 % Whites, 28.9% African Americans, 10.6% Latinos, 3.6% Asians, and 2.1% of Native Americans, Alaskans, Hawaiians, and Pacific Islanders. Among the populaces, about 30% have earned a bachelor's or higher, and the remainders have a high school degree. The median household income in Indiana was estimated at $ 47,642. (U.S. Census Bureau, 2018). While females and males without employment were 47% and 39%, respectively (U.S. Census Bureau, 2018). The state of Indiana has implemented plans to counter the problems of opioid abuse and its health consequences, but despite that, the issue kept growing.

Several researchers at treatment centers have investigated opioid abuse and its correlations with opioid misuse. A growing body of evidence suggested that sociodemographic profiles influenced opioid abuse (Farhat et al., 2015; Gul & Sharma, 2017; Lamptey, 2005; Ranjan et al., 2010; Rather et al., 2013; Simoni-Wastila& Strickler, 2011; Swendsen et al., 2009; Tavares et al., 2004). For instance, researchers have shown that divorced marital status, unemployment, and place of residence are significantly related to drug abuse (Tavares et al., 2004). Additional factors highly linked to drug abuse include being unmarried, having low educational and low occupational levels, and living in rural areas (Gul & Sharma, 2017). Ray et al. (2017) found in their study that respondents aged under 40 years old, and male were strongly correlated with opioid abuse. Despite these findings and the implementation of many programs targeting these variables, the problem of opioid abuse continues to amplify.

This cross-sectional and quantitative study design should be conducted to improve the burden of opioid abuse in Indiana. The purpose of the present study was to assess the potential relationship between sociodemographic factors, health insurance, and successful treatment completion for opioids abusers in Indiana. The outcomes of the study could promote positive social change by expanding health insurance coverage, improving treatment outcomes, and by reducing morbidity and mortality rates due to opioid abuse. In the current chapter, I will discuss the purpose, background, nature, and significance of the study, the problem statement, research questions, and hypotheses. This chapter will also include the theoretical foundation and conceptual framework used, its assumptions, and limitations.

Background of the Study

Opioid prescriptions abuse has emerged as a leading public health concern both globally and nationwide (Bolshakova et al., 2018; McHugh et al., 2014; Oderda et al., 2015). It has been well documented that the use of medical and nonmedical prescription of opioids has increased in the United States for many decades (Bolshakova et al., 2018; Han et al., 2017; McCabe et al., 2017). In 2004, researchers suggested that approximately 2.5 million individuals aged 12 and older had used nonmedical prescription of pain relievers within the past year (Wisniewski et al., 2008). Other researchers noted that nonmedical prescriptions of opioids have surged to 53%and have become accessible for individuals to use (Tetrault& Butner, 2015). Several researchers also discussed the upsurge of medical prescription of opioid in recent years. Meyer et al. (2014) reported large increases in methadone, oxycodone, and hydrocodone prescriptions with 933%, 588%, and 198%, respectively. Furthermore, a survey by Han et al. (2017) indicated that roughly 92 million adults used prescription opioids within the past year and about 12 million of them abused them. The use of illicit prescription opioids has become more fatal (Morales et al., 2019).

Opioid prescription abuse is a significant public health dilemma and can lead to substance abuse disorder and overdose (Bolshakova et al., 2018, and Han et al., 2017; McCabe et al., 2017). Recently, Kolodny et al. (2015) noted that people needing addiction treatment because of OPRs rose to a daunting number of 900%. Gomes et al. (2018) noted that opioid overdose had claimed more than 800,000 lives under 65 years old in the United States. In another survey, researchers revealed that about 75% of the total overdose fatalities were due to prescription opioids (Florence et al., 2016). Morales et al. (2019) estimated the overdose-related mortality in 2017 to reach more than 70,000 people. The burden of opioid abuse continues to grow, despite massive government spending in healthcare. In Indiana, opioid overdose claimed the lives of over 1700 people (Richard Fairbanks Foundation, 2018).

According to Meyer et al. (2007), the total medical costs related to prescription abuse was estimated at $55.7 billion annually. Florence et al. (2016) estimated this figure to be closer to $78.5 billion. Moreover, researchers found that sociodemographic factors were significantly associated with prescription opioid abuse (Farhat et al., 2015; Gul & Sharma, 2017; Lamptey (2005); Ranjan et al., 2010; Simoni-Wastila& Strickler, 2011; Swendsen et al., 2009; Tavares et al., 2004). Researchers revealed that younger people aged 15-24 years and 25-44 years old were the most vulnerable (Gomes et al., 2018). Despite these studies and the implementation of various recommendations, the epidemic of prescription opioid abuse continues to grow. There was a limited research on health insurance coverage and treatment completion for opioids abuse, and this cross-sectional and quantitative study intended to fill the gap. This study is needed to expand health insurance coverage and improve treatment outcomes while reducing morbidity and mortality rates due to opioids abuse in Indiana.

Problem Statement

The upsurge of prescription opioid abuse and its emergence as a leading public health problem had been well documented (American Health and Drug Benefits or AHDB, 2015). In 2007, an estimated 5.2 million individuals aged 12 years and older had been reported to abuse prescription opioids during the past month. About 2.1 million of them initiated nonmedical prescription of opioids (AHDB, 2015). The use of nonmedical prescription opioids had also climbed sharply and had shown to be very dangerous because it could lead to addiction and death (AHDB, 2015). The total costs related to opioid prescription abuse also soared significantly. Birnbaum et al. (2011) noted that the total projected U.S. expenditure linked to opioid prescription abuse was $55.7 billion in 2007 including $25.6 billion (46%) for workplace, $25.0 billion (45%) for health care costs, and $5.1 billion (9%) for criminal justice costs.

Morbidity and mortality related to opioid prescriptions increased dramatically in recent years (Miller et al., 2018). During 2014 and 2015, the number of fatalities linked to drugs accounted for 52,404 deaths nationwide, in which 63.1% involved opioid use (Seth et al., 2018). People aged 24-45 years old were more vulnerable than other age groups (Gomes et al., 2018). Some toxicology tests on unknown sudden deaths have revealed that 86.0% were tested positive to opioid, shifting the mortality rate to 86.0% from 34.2% (Lowder et al., 2018). Data show that individuals aged 18 to 25 years old are more vulnerable than other groups (NIDA, 2018). Many efforts had been implemented to curb the epidemic, but the problem continues to grow unabated. Various studies focused on sociodemographic factors, but few of them are specifically from Indiana, a state of 6.692 million people. Additionally, previous studies failed to evaluate the recently implemented strategies, which may play a role in the intensification of this opioid prescription abuse. There is limited research that evaluated opioid abusers' health insurance status associated with their treatment outcomes. Researchers suggested that individuals with better insurance coverage are more likely to receive specialty substance abuse treatment than those who are uninsured (Cummings et al., 2014). This cross-sectional and quantitative study aimed to assess the association between sociodemographic factors, health insurance coverage, and treatment completion for opioids abusers using the Treatment Episode Data Set – Discharges (TEDS-D). The conclusions of this study could help design policies to expand insurance coverage and to improve opioid treatment outcomes. This could improve morbidity and mortality rates due to opioid abuse in Indiana.

Purpose of the Study

Researchers have found that inappropriate use of physicians' prescription of pain relievers, lack of training, and lack of cooperation among federal agencies are among the main factors that lead to opioid abuse. Additionally, sociodemographic factors play a significant role in the epidemic. Many efforts have been implemented but failed to curb this growing public health concern of prescription opioid abuse. This cross-sectional and quantitative approach aimed to examine the correlation between sociodemographic factors (age, gender, race, education status, marital status, and employment status), health insurance coverage, and treatment completion outcomes for opioid abusers in Indiana using the TEDS-D. The primary dependent variable was "treatment completion" and the dependent variable was "opioids abuse" or "opiates/synthetics abuse." The exposure or predictor variables were sociodemographic factors (age, gender, race, education status, marital status, and employment status) and health insurance coverage.

Research Questions and Hypotheses

Research Question 1: Is there any association between sociodemographic factors and opioid abusers among residents in Indiana?

$H_0 1$: There is no association between sociodemographic factors and opioid abusers among residents in Indiana.

$H_a 1$: There is an association between sociodemographic factors and opioid abusers among residents in Indiana

Research Question 2: Is there any association between health insurance coverage and treatment completion for opioid abusers in Indiana?

$H_0$2: There is no association between health insurance coverage and treatment completion for opioid abusers in Indiana

H_a2: There is an association between health insurance coverage and treatment completion for opioid abusers in Indiana

Research Question 3: Is there any association between health insurance coverage and treatment completion for opioid abusers in Indiana after controlling for sociodemographic factors?

$H_0$3***:*** There is no association between health insurance coverage and treatment completion for opioid abusers in Indiana after controlling for sociodemographic factors

*H*a3***:*** There is an association between health insurance coverage and treatment completion for opioid abusers in Indiana after controlling for sociodemographic factors

Sociodemographic factors were also adjusted to assess their relationship with treatment completion when controlling for age, gender, race, marital status, employment, and education level. The dependent or outcome variables considered in this study were "treatment completion" and "opioids abuse or opiates/synthetics abuse." They were both measured as categorical variables. The independent or predictor variables were "sociodemographic factors" and health insurance coverage and were both measured as categorical.

Theoretical Foundation

Social cognitive theory (SCT) seemed the most appropriate in this quantitative cross-sectional study. SCT was invented by Bandura in 1986 (Glanz et al., 2015). The theory focused on how cognitive, behavioral, personal, and environmental factors interact to determine motivation and behavior (Weaver, 2016). Glanz et al. (2015) noted that SCT had been applied to understand ways individuals may learn about risky behaviors. The model had also been used to attain individual and group-level behavioral changes (Glanz et al., 2015). SCT is an essential public health tool for promoting health and had been effective in managing addictive behavior such as tobacco and alcohol (Glanz et al., 2015). SCT describes that human behavior is generally motivated and regulated by the persisting application of self-influence (Glanz et al., 2015). In Bandura's complete description of SCT, human behavior is elucidated as a triadic and dynamic model of causation through which behavior, personal cognitive factors, and socioenvironmental impacts all interact as reciprocal determinism (Glanz et al., 2015). The self-regulative mechanism functions using one’s self-monitoring, its determinants, and its effects. Self-regulation also embraces one’s self-efficacy, which can promote personal entity through its vigorous impact on thought, motivation, and action (Glanz et al., 2015). The proposed framework had been widely employed to describe the mechanisms by which individuals learn about risky behaviors. Additionally, the model had been used in the initiation and the achievement of individual and group-level behavioral goals and had been effective in community health promotion strategies (Glanz et al., 2015). For instance, the model of SCT had been applied by Tze et al. (2012) to learn about youths' substance drug abuse behaviors and to propose school-based programs to help them resist the drug. The SCT will be applied in the study to help understand how personal behavior and socioenvironmental interact to influence health.

Nature of the Study

The most appropriate research design for this secondary data analysis is a cross-sectional and quantitative study. The rationale for selecting this design was that data in the TEDS-D were collected at one point. An advantage of this type of study, as reported by Sedgwick (2014) is that it allowed the investigator to estimate the prevalence of behavior, which had the potential to drive resources allocation and planning interventions. Also, cross-sectional studies are generally quick, easy, and cheap to conduct, and there will be no missing participants to follow-up because they are interviewed once by using a questionnaire survey (Sedgwick, 2014). However, care is needed if diverse enrollees are included at each time point. It might be hard to evaluate if variations in prevalence reflect a trend or change between different groups of participants selected from the population being studied (Sedgwick, 2014). The SCT of Bandura will be the primary guiding principle of this cross-sectional research approach. A quantitative method will enable the investigator to display data informing about the association between sociodemographic factors, health insurance, and treatment completion for opioid abusers in Indiana. In this study, the outcome variables were “treatment completion” and “Opioid abuse or opiates/ synthetics abuse” and were both categorical. Predictor or exposure variables were sociodemographic factors and health insurance coverage, and both were measured on the categorical level. A survey from the 2017 TEDS-D will be used and descriptive statistics, Chi-square analysis, and multivariate logistic regression were applied to analyze data.

Operational Definitions

Agonists: Are medications designed to activate some receptors in the brain (Indian Health Service [IHS], n.d). There exist full and partial agonists. Heroin, oxycodone, methadone, hydrocodone, morphine, and opium are examples of full agonists (IHS, n.d). Whereas buprenorphine is an illustration of partial agonist (IHS, n.d).

Antagonists: Are medications that have the potential to block opioids by attaching them to the receptors without causing any opioid effects. Naltrexone and naloxone are good examples of antagonists.

Analog: Medicines that have similar chemical structure with another medicine, but are not identical (CDC, 2019).

Chronic pain: refers to pain that persists up to 3 months or more and such pain can be triggered by an event, condition, injury, treatment, or it can be unknown (CDC, 2019).

Drug abuse: refers to illegal use of drugs or prescription drugs intended for other purposes and not directed by a physician, often in greater amounts, longer than expected, and most often by someone else's prescription (CDC, 2019).

Drug addiction: Drug addiction refers to the persistent chronic use of drug regardless of serious negative socioeconomic and health consequences and is related to loss of control over drug use (Cami and Farre, 2003).

Drug dependence: refers to constant use of drug, triggering the neurons to be accustomed to so that they can only function when the drug is present. When the drug is absent, this can lead to abnormal physiological reactions that can range from mild (in the case of caffeine) to potentially life-threatening situations (in the case heroin) (NIDA, 2019].

Fentanyl: Pharmaceutical drug (synthetic opioid) designed to treat severe pain such as in advanced cancer. The drug is 50 to 100 times more powerful than morphine. Nonetheless, there exist illegal made fentanyl which can be sold on black markets generating heroin-like effect to users, but can be dangerous and very fatal (CDC, 2019).

Fentanyl analogue: Fentanyl analogues are drugs manufactured clandestinely and synthesized to yield similar psychotropic reactions to regular fentanyl, but come with slightly different molecular structures, making the screening more challenging for the investigator (Cabrices et al., 2018).

Heroin: Aprohibited and very addictive opioid drug that is processed from morphine and obtained from some poppy plants (CDC, 2019).

Illicit drugs: The non-medical drugs that remain illegal by law. There are many drugs, and it includes amphetamine, marijuana/cannabis, cocaine, heroin, other opioids, and synthetic drugs like illicitly manufactured fentanyl (IMF) and ecstasy (CDC, 2019).

Licit drug: non prohibited drugs and it includes drugs prescribed by a physician including the recipient's instruments for whom the drug is intended to, and this also incorporates drugs used for treatment of a disease and over the counter medicines when they are used appropriately (Brecher, 2016).

Long-Term residential treatment: Health service that provides care for 24 hours daily, often in non-hospital setting, and with concerned individuals willing to stay for treatment for a period between 6 and 12 months (NIDA, 2018).

Morbidity rate: Morbidity refers to any subjective or objective departure, from a state of physiological or psychological well-being. It involves disease, injury, and disability, and focuses on the number of sick people. Sometimes, this can be referred to the periods of sickness that these individuals experienced, or the length of their sickness (CDC, 2012).

Mortality rate: this is referred to the measure of the frequency of occurrence of loss of life in a specified population within a specific time (CDC, 2012).

Narcotic drugs: this term referred to any substance that is intended to relieve pain. The term is sometimes applied to all prohibited drugs but theoretically, the term is merely referred to opioids. Now opioid becomes the ideal term to avert confusion (CDC, 2019.).

Nonmedical use: the use of any prescriptions prescribed by a physician, prescription drugs that are diverted (drugs not intended to another person to use), for any purpose, in any amounts, or in specified time-period the drug is prescribed (CDC, 2019).

Opioids: refers to a class of medicines that involves prohibited drugs such as cocaine, heroin, synthetic opioids (e.g., fentanyl,) and pain killers that are available by medical prescription (e.g. oxycodone, hydrocodone, codeine, morphine, and lots of others designed to lessen the intensity of body pain. Opioids' prescriptions are usually safe when used in short period of time and when the prescription is used as instructed by a physician. Nonetheless, because such prescriptions trigger euphoria besides their pain relief effects, they are subjected to abuse and can lead to addiction (CDC, 2019).

Opioid abuse: the term is generally applied when one's body tends to adjust its regular operation or functioning towards routine use of opioid. Some unpleasant symptoms can appear when the person is no longer using the drug (CDC, 2019).

Opioid overdose: the use of opioids can affect the brain that controls the respiratory system. As a result of taking greater amount of opioids, this leads overdose, which can slow down the respiration process, and in some cases can stop it suddenly, which can lead to death (MedlinePlus, 2019).

Opioid use disorder (OUD): the term refers to usual or abnormal pattern of opioid use that can trigger body impairment. A person is considered to have OUD after unsuccessful efforts or attempts to reduce or curb its use, or when the excessive use of the drugs can result in many social troubles including absenteeism at workplace, school, or prevent a person to fulfill normal obligations at home. The term "opioid use disorder or OUD" is ideal term, especially when used with similar definitions, "opioid abuse or dependence" or "opioid addiction (CDC, 2019).

Prescription diversion: Prescription drug diversion is an illegal channeling of regulated pharmaceutical substance or drugs from lawful sources to illegal marketplace (Wood, 2015).

Prescription opioids: People use prescription opioids to treat or overcome moderate-to-severe pain and these prescriptions are often recommended after surgery or injury, or they are sometimes intended for serious health conditions such as cancer (CDC, 2017).

Short-Term residential treatment: the term short-term residential treatment involves intensive but somewhat short treatment related to a modified 12-step approach. The conventional residential treatment model entailed a 3- to 6-week inpatient treatment (hospital-based) which is followed by a prolonged outpatient rehabilitation that necessitates focus group participation (NIDA, 2018).

Sociodemographic factors: It is referred to a group defined by its sociological and demographic profile. It looks at the life around individuals' characteristics such as age, gender, one's sexuality, race, religion, income, matrimonial status, birth rate, death rate, average size of family, heritage, level of education, medical history and so on**.** It is basically a grouping of people by those characteristics (Stone, 2016).

Substance abuse: refers to the use of psychoactive substance or drugs that can provoke harm or causes hazardous effects on the affected individuals, including people who use alcohol and illicit drugs (WHO, 2020).

Substance dependence: the term substance dependence refers to one's inability to function without the use of an illegal drug or substance. This state is indicative of body impairment under the use of illicit substances (APA, 2000).

Substance use disorder refers to a state of brain impairment that causes a person's inability to control the use of a lawful or unlawful substance or medicine. Among others alcohol, marijuana and nicotine are also considered drugs (Mayo Clinic, 2020).

Treatment intervention: the term treatment intervention refers to the coherent and accurate conceptualization of health services delivery, and such treatment is used as planned (Hart, 2009).

Assumptions

In this cross-sectional and quantitative research, it is assumed that substance abuse is understood and successfully cured when the person involved (user or abuser) is judged in the context of one's family unit or in a secure living group. This point of view is considered vital in the protection of individual from substance abuse, and this viewpoint is assumed in the study. It is also assumed that behavioral patterns, attitudes, beliefs, and values in the society are discernable and that participants understand and share these patterns. Additionally, it is accepted that the recorded responses or answers in the TEDS-D survey were the most straightforward and honest. Moreover, it is assumed that participants in this cross-sectional survey understood well the idea of substance abuse and its underlying consequences like substance abuse disorder (addiction).

Scope and Delimitations

For this survey, the emphasis was put on the various sociodemographic factors that might be connected to opioid abuse along with health consequences, including overdose, addiction, and substance use disorder. This survey's sociodemographic factors are defined as age, gender, race, marital status, education, and employment status. Using TEDS-D, the variables included in this analysis were sociodemographic factors, health insurance status, and treatment completion for opioid abusers in Indiana. This study excluded individuals under 18 years old and all missing cases in the dataset. Only

Treatment Episode Data Set -Discharges or TEDS-D were employed to carry out this analysis. It is a national survey instrument that collects subjects' substance abuse information, including demographics, admissions, and discharges. Information gathered in the TEDS was accurate, and all states and local jurisdictions receiving federal funding participate in the survey. The researcher extracted Indiana information from the TEDS for analysis of the variables of interest. It appeared that such data contain fewer missing cases making the data more reliable. But the researcher will use multivariate regression analysis to minimize potential bias from the TEDS.

Limitations

This cross-sectional survey might not be conducted without limitations. Because of the nature of data collection, information bias might be introduced via participant self-report. Self-reporting, a widely used approach for gathering data, and requires participants to respond to the researcher’s questions without any interference. Self-reporting data represents a problem for most research design, including cross-sectional’s (Althubaiti, 2016). Substance Abuse and Mental Health Services Administration [SAMHSA] (2019) reported that external factors such as lack of funding could influence this study's validity. It has been shown that states receiving higher funding tend to admit many substance abusers for treatment (SAMHSA, 2019). Some states also reported more admissions for the same person, which means information gathered represented admissions instead of the patient (SAMHSA, 2019). Nonetheless, some missing data were recorded in Indiana. Statistical analyses such as multivariate regression will be applied to minimize external threats.

Significance of the Study

The relationship between sociodemographic factors, opioids abuse, and the resulting health consequence of opioid use disorder has been well established (Tavares et al., 2004; Lamptey (2005); Swendsen et al., 2009; Ranjan et al., 2010; Simoni-Wastila& Strickler, 2011; Farhat et al., 2015; and Gul & Sharma, 2017). A mountain body of evidence suggested that prescription opioid abuse can be deadly. Opioid overdoses claimed over 70,237 people in 2017 alone, and 2/3 of them (47, 600) implicated opioids (CDC, 2019). Common licit drugs used in opioid overdose mortality include Methadone, Oxycodone, and Hydrocodone (CDC, 2017). Also, data showed that illegal drugs, including methamphetamines, fentanyl, and heroin, play a deadly role, too (NIDA, 2019). The prevalence of fatal opioid overdoses in Indiana claimed 1,104 lives in 2018 (Richard Fairbanks Foundation, 2018). Individuals aged 18 years old and over were more vulnerable than any groups (NIDA, 2018). About $ 56 billion were spent yearly in prescription of opioid misuse or abuse in the U.S (Birnbaum et al., 2011). To date, few researchers have assessed the association between health insurance and treatment outcomes. This cross-sectional survey aimed to fill the gap. When the study is completed, and its recommendations are implemented, it will promote positive social change by expanding substance users' coverage and improving their treatment outcomes in Indiana. Additionally, the results of the study will help reduce morbidity and mortality due to opioid abuse.

Implications for Positive Social Change

When this cross-sectional study is completed, the outcomes might have several practical implications for positive social change. The findings could improve healthcare professionals' knowledge about specific sociodemographic factors contributing to opioid abuse while increasing opioids abuse screening in clinical settings in Indiana. The results provide an opportunity for health professionals to target those most vulnerable by raising awareness. Moreover, the study's completion would enable policymakers to expand health insurance coverage for substance abusers who are uninsured or underinsured. Additionally, this research could help facilitate access to treatment centers for drug abusers. Most importantly, the results can lay the foundation for increased cooperation among services to tackle the epidemic of prescription opioid abuse and reduce morbidity and mortality due to opioids.

Summary and Transition

Prescriptions of opioid have become one of the leading public health problems in the United States and in Indiana. It has been demonstrated that opioid abuse can lead to fatal overdose and substance abuse disorder. More than 2/3 of individuals who overdose involve opioids. Evidence also suggested that the total healthcare expenditure due to opioids were estimated at $ 55 billion annually. Sociodemographic factors have shown to be linked to opioids abuse. Few studies have been conducted about insurance coverage and treatment completion for opioid abuse. This study will fill the gap and assess the correlation between insurance coverage and treatment completion. The outcomes of the study will help expand coverage for substance abuse and improve the treatment outcomes in Indiana. Various intervention plans have been put forth to tackle this growing issue of opioid abuse. Despite this, the problem continues to grow unabated. The next chapter (chapter 2) will offer an overview of literature review including (a) scope of prescription drug abuse, (b) burden of opioid abuse, (c) sociodemographic characteristics and opioid abuse, (d) health insurance and substance abuse treatment (e) research involving drug treatment (f) treatment options for opioid abuse (g) existing policies for opioid abuse, and (h) Summary.

Chapter 2: Literature Review

Opioid abuse has been a long-standing public health issue that the United States faces for many years. The societal cost burden of opioid misuse was estimated at $78.5 billion in 2013, and the number continues to grow since (Florence et al., 2016).As of 2013, nearly 2 million individuals reported prescription opioid abuse in the U.S. (Florence et al., 2016).It is widely recognized that prescription drug abuse or misuse has been expanding dramatically nationwide during the last decade, and younger adults aged 18 to 25 years remain the most vulnerable. It has been documented that licit prescription drug such as hydrocodone and oxycodone are the most misused substances among young adults. The use of prohibited substances including heroin, cocaine, methamphetamine, and fentanyl has also been shown to be rising over recent decades (Chaturvedi et al., 2009). Schrager et al. (2014) noted that prescription of opioids has become a growing public health problem because its abuse or misuse has demonstrated to have a host of negative health consequences like fatal opioid overdoses.

Similar opioid abuse trend has been seen in Indiana despite spending $43 billion, and implementating local government restrictions on opioid prescription (Richard Fairbanks Foundation, 2018). In 2017, the overdose-related fatalities in Indiana were estimated at 1,700 deaths (Richard Fairbanks Foundation, 2018). In the same year, an estimated 355 people died from overdose and the bulk of it was attributed to opioids (Richard Fairbanks Foundation, 2018). The main purpose of this quantitative research study is to assess the correlation between sociodemographic factors (age, gender, race, education, employment status, and marital status) and treatment completion for opioids' abusers in Indiana. The assessment of the correlation between health insurance status and successful treatment completion for opioid abuse was unexplored. The current study is going to fill the gap. In this chapter, I will discuss the search strategy regarding the sources of interest to develop a literature review and the theoretical foundation/conceptual framework on which the investigation was built on.

Literature Search Strategy

Numerous databases were searched to perform the literature review in this study. The search strategy included PubMed, Google, Google Scholar, EBSCO, Academic Search Premier, ProQuest, Allied Health Source, books, scholarly journals, and Medline. Some advanced searches have been applied from Walden University library to carry out the review. Also, published reports and articles from Federal and local governments websites such as CDC, the Indiana State Health and Marion County health departments, the National Institute on Drug Abuse (NIDA), as well as the Indiana University School of Public Health, the Department of Health and Human Services, and the World Health Organization websites were consulted.

Phrases and search words used in this literature search strategy include sociodemographic factors, drug abuse, and factors contributing to drug abuse or addiction. Also, the review has used wording such as mortality, morbidity, opioid abuse, opioid addiction, dependence, nonmedical substances, medical substances, licit substances, illicit substances, substance use, drug addiction, substance abuse, association, correlation, relationship, economic cost, health insurance coverage, treatment completion, and financial burden. Sometimes, advanced searches have been conducted to yield meaningful articles used in this literature review (e.g., sociodemographic factors and opioid abuse, opioid, and D.P.H). This search strategy has enabled to retrieve relevant articles from 2004 to current.

Given the scope of articles of interest, the researcher proceeds into the selection of these sources that meet the search criteria before placing any consideration. This enables the investigator to move with valuable information from relevant articles for more credible literature review. The criteria for inclusion in the search are opioid prescription abuse and sociodemographic factors. This enabled to retrieve only sources focusing on opioid abuse and its sociodemographic influences. The words opioid misuse, dependence, and addiction were avoided to prevent confusion in the search outcomes since the study was only concerned with opioid abuse.

Theoretical Foundation

The theoretical framework in this study will be based on SCT invented by Bandura in 1986. The SCT will be applied in the survey to help understand how personal behavior and socioenvironmental interact to influence health. SCT enables one's behavior to be largely motivated and regulated by the persistent use of self-influence (Glanz et al., 2015). In Bandura's complete description of SCT, human behavior is elucidated by three constructs such as behavior, personal cognitive, and socioenvironmental factors. They all interact as reciprocal determinism (Glanz et al., 2015).

The use of SCT in health issues demands a clear understanding of reciprocal triadic factors including personal cognitive factors, socioenvironmental, and behavioral factors) (Glanz et al., 2015). Personal cognitive refers to the person's aptitude to self-direct, self-regulate, and evaluate contextual situations. Glanz et al. (2015) identified three constructs related to personal cognitive factors. Confidence to get involved in a certain behavior (self-efficacy) is one construct. The capacity of foreseeing the outcomes of behavior patterns (outcomes expectations) is another construct. Finally, there is the skill gained to enact a behavior (knowledge) [Glanz et al., 2015]. Socioenvironmental determinants refer to physical environmental aspects that promote, allow, or refusal to engage in a specific behavior. Socioenvironmental aspects involve observational learning, cultural beliefs to the acceptability of a given behavior (normative beliefs), social support, and the easing of health behaviors (opportunities and challenges) [Glanz et al., 2015]. Behavioral determinants or factors impact the health directly. Health behaviors involve health-enhancing actions that lead to people's health improvement or poor actions leading to poor health (Glanz et al., 2015). Behavioral determinants involve the individuals' health behavioral abilities (coping skills), their goals for behavior change (intentions), and the rewards for espousing a healthy behavior (reinforcement) [Glanz et al., 2015]. Glanz et al. (2015) noted SCT proposed that deterrence of mortality and morbidity via the increase of healthy behaviors and the lessening of unhealthy ones are accomplished through the change in these triadic factors (personal cognitive, socioenvironmental, and behavior) [Glanz et al., 2015].

In SCT, goals are important in changing behavior. Bandura (2004) states that intentions are considered as goals since performing an action require individuals to engage in appropriate behavior. Bandura (2004) highlighted the use of goals in SCT.

When highly valued, goals have the potential to stimulate motivation towards adopting healthy behavior practices. Setting goals is one of the most appropriate steps in health behavior change.

Social learning plays an essential factor in individuals' substance abuse. This has been demonstrated by Tze et al. (2012) suggesting that students are educated to resist the drug abuse in a school-based prevention program, leading a substantial reduction of drug use among them. Tze et al. also noted school-based programs often apply the model because of the influences of social determinants on adolescents' development and adolescents' susceptibility to higher risk behavior of substance abuse. The principle of the social-cognitive theory is that youths in substance abuse circumstances detect drug-using peers and start to observe and imitate drug use behaviors (Tze et al., 2012). Evidence revealed that when an adolescent observes a friend using drugs, he or she may change their beliefs and attitudes to using a drug (Tze et al., 2012). Similarly, non-drug users may experience drug use when engaging with individuals who use the drug. Tze et al. noted that when a group of close friends maintains a positive attitude toward substance abuse, non-drug users will be less willing to engage in drug use. However, other researchers refuted such correlation (Tze et al., 2012).

Self-efficacy is another concept of SCT. It is a contextual assessment of a person confidence to perform a task. Besides, self-efficacy has a crucial role in individuals' capability to be involved in high-risk behaviors (Tze et al., 2012). According to social cognitive theory, individuals' self-beliefs regarding substance abuse influences their actions (Tze et al., 2012). Moreover, individuals' capacity to self-direct and self-regulate has shown to affect their behaviors. That is, individuals' self-efficacy to reject substance abuse are less likely to use drug. The higher the self-efficacy, the lower ability to engage in drug abuse (Tze et al., 2012). Therefore, self-efficacy has a protective effect on individuals drug use.

Tze et al. (2012) noted that individuals' self-efficacy of substance use plays a significant role in changing them towards drug-using behaviors. Tze et al. cited evidence from previous studies that showed a strong association between social learning and self-efficacy. It noted that when adolescents are exposed to free cocaine from friends and know how to inhale it, they will use it (Tze et al., 2012). That is, exposure to drug use by non-users can influence them and their substance use self-efficacy can rise just by observing others.

Self-regulative mechanism functions through one's self-monitoring behavior including its determinants and its effects. It is the use of one's behavior that leads to the interactions between personal standards, environmental circumstances, and affective self-reaction. Besides, self-regulation can embrace the self-efficacy mechanism, which promotes the use of personal entity through its effect on thought, motivation, and action (Glanz et al., 2015). This implies that drug abuse can be explained as behavior that is influenced by the user's predisposed environment. Thus, personal determinants influence the behavior of the user.

This SCT has been employed to many disorders, including the use of psychoactive substances. A study by Bennett et al. (2018) had applied the SCT model to predict medication compliance in patients suffering from depression in the United States in 2016. This cross-sectional research design by Bennett et al. (2018) reported that self-control for taking medication for depression and expectations for taking medicine for depression were statistically significant with $p<0.05$. However, the researchers suggested that the integration of new models was necessary to bolster the SCT constructs (Bennett et al., 2018). Another study by Biro et al. (2017) used SCT to reduce stress in Hungarian college students. Expanding knowledge about psychoactive substances use to lessen stress and developing skills for stress reduction and management approaches are among the strategies used (Biro et al., 2017).

The theoretical framework has proven to be useful in explaining behaviors related to drug use and understating personal actions for change. According to Glanz et al. (2015), SCT explains reasons for individuals to acquire and maintain healthy behaviors. It has also been used by researchers and practitioners to help them determine factors that stimulate health behaviors and to promote strategies for behavior change (Glanz et al., 2015). For instance, da silva and Serra (2004) and Tze et al. (2012) applied the theory to understand factors that motivate drug use in individuals and promote preventive plans.

However, Bandura's SCT model has several limitations in the public health field. The theory assumes that changing environment leads systematically to changes in individuals, which is not always true (LaMorte, 2018). The theory seems loosely organized around personal, behavior, and environment, and does not clearly states whether one determinant has more influence on the others. The theory does not emphasize on motivation but rather on previous experience. Despite, Bandura's SCT has been widely applied in public health initiatives, especially in substance abuse.

In Giovazolias & Themeli (2014), researchers noted social cognitive theory self-efficacy and outcome expectancies are two cognitive processes that influence a person's behavior. Self-efficacy refers to the evaluation made by the individual relative to one's ability to perform an action in a certain situation. And outcome expectancy refers to one's beliefs that change in their behaviors may lead to desired outcomes or not (Giovazolias & Themeli, 2014). The outcome expectancies are acquired through direct experience of a certain behavior or via observation. Giovazolias & Themeli (2014) noted that the theory of social cognitive learning is used in substance use to assess outcome expectancies and have this theory for effective therapeutic interventions.

Heydari et al. (2014) also examined the role of SCT in addiction quitting. According to the study, the purpose of addiction treatment is to help the client to admit addiction as a disorder and change in lifestyle can prevent the disease progress (Heydari et al., 2014). Heydari et al. (2014) found that using SCT can be effective in assisting individuals quit the addiction.

I used the social cognitive theory (SCT) to help elucidate the outcomes of this quantitative research. The proposed framework has been widely employed to describe the mechanisms by which individuals learn about risky behaviors. Additionally, the model has been used in the initiation and the achievement of individual and group-level behavioral goals and has been effective in community health promotion strategies (Glanz et al., 2015). The SCT will be applied in this quantitative cross-sectional study to help understand how personal behavior and socioenvironmental interact to influence health.

Conceptual Framework

The framework in this research is based on the philosophical worldviews for their influence in the research practice and need Creswell (2014). Four frameworks for research have been identified by Creswell (2014). This includes postpositivism/positivism, constructivism, transformative, and pragmatism (Creswell, 2014). The term positivism refers to a set of scientific research practices, and the concept of knowledge, social reality, and of science (Riley, 2007). Positivism assumptions seem to represent the traditional form of research (Creswell, 2014). Positivism seems the most appropriate framework for this research. According to Creswell, positivism is seen as an approach for quantitative research. Positivism is related to various schools of thought, including empiricism, naturalism, behaviorism, scientism and determinism, and reductionism. It is reflected as a deterministic philosophy in which causes determine effects or outcomes (Shah & Al-Bargi, 2013). As a result, the issues investigated in this framework reflect the importance of identifying and assessing the origins (causes) that influence the outcomes (Creswell, 2014). This suggests that even though people may or may not know what causes them to abuse the drug, they would try to find out these causes and identify corrective actions.

Based on the information described above, the Social Cognitive Theory (SCT) seemed the most appropriate in this quantitative cross-sectional study. The Theory focuses on the interaction between cognitive, behavioral, personal, and environmental factors to establish motivation and behavior (Weaver, 2016). Glanz et al. (2015) noted that SCT had been applied to understand ways individuals may learn about risky behaviors. The model had also been used to attain individual and group-level behavioral changes (Glanz et al., 2015). SCT is an essential public health tool for promoting health and had been effective in managing addictive behavior such as tobacco and alcohol (Glanz et al., 2015). Similarly, SCT will be applied in this research to understand the sociodemographic factors, health insurance status associated with opioid abuse and treatment completion in Indiana residents to promote effective intervention plans.

Literature Review

Scope of Prescription Drug Abuse

According to McCabe et al. (2017), medical and nonmedical use of prescription opioids has been a prominent problem nationwide for many decades. Other researchers revealed a sharp decline in the use of medical and nonmedical opioids (Kolodny et al., 2015). The use of medical prescription opioids has demonstrated to be significantly associated with nonmedical use; Findings revealed that male adolescents have more likelihood to report both medical and nonmedical use of prescription opioids. Also, the study suggested that adolescents were more willing to initiate a medical prescription opioid before they initiated nonmedical prescription opioid (McCabe et al., 2017). The study by McCabe et al. (2017) noted that the increase in opioids prescription could have far-reaching opioid-related health consequences such as illegal use, opioid use disorders or addiction, high rate of emergency department visits, and overdose casualties. Also, a literature review by Bolshakova et al. (2018) noted that prescriptions of opioid had increased tremendously both nationally and globally in recent. While opioid can be used for the treatment of pain in minor and major conditions, prolonged use of it could be associated with increased risk of addiction, overdose, and significant psychological distress (Bolshakova et al., 2018). Similar trends were also found by Kolodny et al. (2015) and Oderda et al. (2015).

The aim of McCabe et al. (2017) study was to investigate the trends of both medical and nonmedical use prescription opioids nationwide among high school seniors. The researchers used the Monitoring the Future (MTF) study for 135 schools to examined 40 independent cohorts, applying random-sampling method. The MTF evaluates a host of behaviors, attitudes, and beliefs (McCabe et al., 2017). Among the major findings of the study, the Pearson correlation to assess medical and nonmedical use of prescription opioids (NUPO) demonstrated higher prevalence in black adolescents than whites' adolescents with respectively ($r = 0.79$, $P < .001$) and ($r = 0.65$, $P < .001$). Earlier studies have revealed that female showed higher medical and NUPO use of prescription opioids, contradicting the findings of the current study (McCabe et al. 2017). One of the strengths of the study is that it highlighted the need for clinical opioid screening in adolescents to tackle the growing drug and mental disorders. A weakness of this cross-sectional study is self-reporting, which may lead to response distortion. I choose the article because it highlighted the role of both medical use and NUPO, which represent a damning concern for American society and for adolescents. The current study goes further to evaluate the association between sociodemographic factors, health insurance coverage and treatment completion for opioids abuse.

Wisniewski et al. (2008) also assessed the correlations between medical opioid prescription, NUPO, and emergency department visits. The purpose of the research was to explore the associations between prescription trends for hydrocodone, oxycodone, and morphine and indicators of nonmedical use and potential consequences in ED visits. Studies suggested that the trend of medical prescription of opioid analgesics has been increasing exponentially since the 1990s and that more hydrocodone combined with acetaminophen has been prescribed than any other drugs (Wisniewski et al., 2008). Researchers in this study noted that in 2004, about 2.4 million individuals12 years old and above have initiated nonmedical use of prescription of pain killer during last year, and evidence showed the use of such prescription drug was correlated with hydrocodone, codeine, propoxyphene, and oxycodone-containing products (Wisniewski et al., 2008). However, Meyer et al. (2014) reported a higher rate of 900%, 600%, and about 200% for methadone, oxycodone, and hydrocodone, respectively. Also, individuals using prescriptions of opioid analgesics have reached 79.5 million nationwide (Meyer et al., 2014).

Wisniewski et al. (2008) used a cross-sectional design to analyze four national databases including the National Hospital Ambulatory Medical Care Survey (NHAMCS), National Ambulatory Medical Care Survey (NAMCS), The Drug Abuse Warning Network (DAWN), and the National Survey on Drug Use and Health (NSDUH). Findings in the study found that medical use and nonmedical use of hydrocodone and oxycodone and ED visits were correlated and statistically significant yielding a p-value < 0.04. Similarly, male sex, the White race, and age older than 35 were predictors of hydrocodone and oxycodone prescriptions with p-value < 0.0001 (Wisniewski et al., 2008). A strength of the study was that the findings might have far-reaching medical implications. The outcomes of the study highlighted the need for prescribers to pay close attention to opioid prescriptions because it may be diverted for nonmedical use. That is, physicians could limit or restrict opioid prescriptions to their patients to reduce prescription abuse. A weakness of this cross-sectional study was that secondary analysis does not establish cause and effect association by its nature. This article is relevant because of its focus on the relationship between opioid prescribing, nonmedical use, and emergency department visits. The current secondary data analysis will expand the knowledge and explore the association between health insurance coverage and treatment completion for opioids' abusers.

The United States has been experiencing for decades the problem of prescription opioid abuse and the underlining consequences of it, including overdose fatalities and substance abuse disorders continue to grow unabated. In the survey conducted by Han et al. (2017), researchers evaluated the prevalence of prescription opioid use, misuse, and use disorders and assessed motivations that lead to the abuse among U.S. adults. The survey suggested that nearly 91.8 million adults, accounting for 37.8% have used prescription opioids within the prior year. Among them, 11.5 million individuals (4.7%) abused them and 1.9 million (0.8%) developed substance use disorders (Han et al., 2017). Synthetic fentanyl is another form of deadly opioid that users are suddenly facing (Morales et al., 2019). Han et al. (2017) noted that the risks for abuse or misuse have complicated opioid prescriptions. The study used a cross-sectional design from the 2015 National Survey on Drug Use and Health (NSDUH) to collect data. A large sample entailing72 600 adults were selected for NSDUH, and 51 200 showed to complete the survey interview. Probability sampling methods have been applied in the study. Major findings of the survey revealed that among those who abused prescription opioid, 63.4% cited relief from physical pain as the reason while 47.8% of opioid use disorders cited pain relief as the main motivation. The conclusions of the research are consistent with earlier surveys (Han et al., 2017).

Also, among participants who abused or misused prescription opioids, almost 2/3 (59.9%) obtained them without a prescription at least once, and 40.8% got them from a relative (Han et al., 2017). However, a survey reported that 53% of prescription opioids for nonmedical use are easily accessible for friends or relative, 15% were bought from a friend, 21% prescribed by a physician, 3% prescribed by many doctors, 4.6 percent brought by drug dealer, less than 1% through internet purchased, and 4% via forgery (Tetrault & Butner, 2015). The findings may have practical implications since they highlighted the need for implementing policies that target medication sharing, selling, and diversion. However, the limitation of the study was that it reported a lower response rate, increasing the potential for nonresponse bias (Han et al., 2017). The article seemed relevant because it highlighted the significance of opioid prescription abuse, and it recognized the outcomes of such abuse (e.g., substance abuse disorders) while hinting for intervention strategies. Similar patterns had been reported by Bolshakova et al. (2019). Finally, a study by Strain et al. (2019) evaluated the epidemiology, pharmacology, signs, testing, and detection of opioid use disorder. Strain et al. (2019) noted that opioids are applied to treat medical conditions and to alleviate pain. Opioids may contain analgesic and may cause the central nervous system to depress. Opioid prescription abuse can lead to opioid use disorder (OUD) which is linked to high morbidity and mortality (Strain et al., 2019).

McHugh et al. (2014) noted that prescription drug abuse became a growing health issue in the nation. In this study, McHugh et al. (2014) aimed to explain a sampling of the recent research related to prescription drug misuse or abuse ranging from its epidemiology, correlates, intervention outcomes, and from policy perspectives. The study suggested that between 1990 and 2000, nearly 3 million initiators of abuse in prescription occurred annually. The abuse in prescription drug has been increasing in recent years. McHugh et al. (2014) stated that opioids were the most frequently abused substance and had contributed substantially to the current crisis.

McHugh et al. (2014) noted that the National Survey on Drug Use and Health believed that nearly 17 million individuals 12 years old and above had misused prescriptions nationally in 2012. About 2.1 million individuals align with the identification of a substance use disorder related to prescription drugs. Also, the number of adults who abused prescription of opioids went up from approximately 5 to 12.5 million from 1992 to 2012. The paper noted that prescription of opioid use led the pack of drug abuse disorders, and ranked second after alcohol (McHugh et al., 2014). The study also noted that prescriptions of opioids abuse were correlated to a range of factors such as poor performance in school, violence, delinquent behavior, and psychological disorders (McHugh et al., 2014). The authors of this study used a collection of literature to review prescription of substance abuse from epidemiology standpoint to public policy perspectives. The strength of this study was that it highlighted the growing issue of prescription of drug abuse, most importantly, the prescription of opioid abuse and its health consequences and overdose fatalities in the United States. The study revealed further the need to improve training for prescribers, the prescription monitoring system, and accessibility to treatment centers (McHugh et al., 2014). One weakness of the study is that it does not elucidate the approaches used to collect data. The current cross-sectional study will look further to assess the realtionship between health insurance coverage and treatment completion for opioids abuse to design policies to solve this growing public health problem.

Prescription drug abuse (PDA) is not only emerging as a leading puclic health problem in the U.S., but also in Indiana. Oderda et al. (2015) noted that prescription drug abuse or PDA, particularly opioid abuse has been recognized as the fastest-growing threat to American society and has been classified as an epidemic according to the Centers for Disease Control and Prevention. This study noted that in 2013 alone, nearly 15.3 million people (about 6% of the population) reported using drugs for nonmedical reasons, citing pain relievers as the most common reason. Oderda et al. (2015) noted that between 11,660,000 and 20,660,000 people used illicit drugs once in the year of 2009 (Oderda et al., 2015). The total prevalence of opioid dependence in North America has been estimated at 0.30% (Oderda et al., 2015). But, in Indiana, providers prescribed 74.2 opioid prescriptions for every 100 persons in 2017 compared to 58.7 prescriptions across the United States (National Institute on Drug Abuse, 2019). In 2010, the rate was even higher, with 107.1 prescriptions of opioids per 100 people (NIDA, 2019).

Using a systematic review, the purpose of Oderda et al. (2015) was to analyze various data and summarize published evidence of the prevalence of prescription opioid abuse as well as its health consequences and societal costs. In this systematic review, a Population, Intervention, Comparator, Outcome, and Timeframe format or PICOT was applied and examined 5,281 citations. The study by Oderda et al. (2015) highlighted the significance of opioid abuse, the related costs, and health consequences. The researchers in this review used appropriate approaches because the findings provided an overview of the prevalence of opioid prescription abuse, the costs, and health consequences. However, large missing data in the evaluation could impact the validity and reliability of the findings. If the data were completed, it might lead to different conclusions. However, this current study will further explore the correlation between health insurance and treatment completion.

Burden of Opioid Abuse

Opioid prescription abuse and its overdose fatalities are becoming one of the major public health issues in the nation and particularly in Indiana. Previous studies found that approximately 1 million disability-adjusted life-years were attributed to opioid dependence (Gomes et al., 2018). In Gomes et al. (2018), the investigators also revealed that over half of the disability-adjusted life-years are due to years of life lost or YLL. In a cross-sectional design study, Gomes et al. (2018) investigated the problem of opioid-related mortality throughout the nation over time and had noted that prescription opioid overdose was responsible for 830, 652 YLL among individuals under 65 years old. The study indicated that the dramatic increase in opioid-related mortality rate could be attributable to the recent use of fentanyl and other illicit opioids (Gomes et al., 2018). Florence et al. (2016) also noted that prescription opioids account for roughly 70% of drug overdoses fatalities. The survey by Gomes et al. (2018) applied the Centers for Disease Control and Prevention (CDC) WONDER Online Database to capture mortality and population estimates by age and gender.

Results from Gomes et al. (2018) indicated that 335, 123 people with opioid-related mortality in the United States fit the standard selection and noticed a 345% increase from 33.3 deaths per million population in 2001 to 130.7 deaths per 1,000,000 people in 2016. Males were the most vulnerable, accounting for 67.5% of all opioid-related mortality, and having a median for age of 40. More alarming, the proportion of opioid death-related went up from1 in every 255 (0.8%) to 11 in 65 (1.5%) [Gomes et al., 2018]. Nonetheless, the highest absolute increase was seen among individuals aged 25-34 (from 4.2% in 2001 to 20% in 2016). Individuals aged 14-24 years were ranked second from 2.9% to 12.4%, respectively, in 2001 and 2016 (Gomes et al., 2018). The findings revealed that deaths related to opioids abuse accounted for 5.2 YLL per 1000 people in the United States for the year of 2016, with males being the most affected. Additionally, those aged 25 to 34 years and 35 to 44 years have the highest prevalence of opioid-associated mortality accounting for 12.9 YLL per 1000 people and 9.9 YLL per 1000 people, respectively (Gomes et al., 2018). These findings are significant because it calls for interventions targeting the most vulnerable population, as shown above. A limitation of the study was the definition used in the analysis, which impacts the validity of the overall outcome. The article is relevant because it discussed the burden of opioid-related deaths in the United States, showing opioid prescription abuse and its consequences to be one of the most pressing issues across the nation. The present study will expand further to assess the association between health insurance coverage and treatment completion for opioids abusers.

Also, Kolodny et al. (2015) noted that high mortality rate had been associated with using opioid pain relievers or OPRs for alleviating pain, which has exacerbated the ongoing health epidemic. Earlier studies have reported that the prevalence of OPRs use nationwide has climbed over the last decade. According to the literature, the consumption of hydrocodone and oxycodone has jumped to 500% from 1999 to 2011. OPR-related overdose fatalities have reached four times high during the same period. The unprecedented public health issue has forced the Centers for Disease Control and Prevention to label it the “worst drug overdose epidemic in U.S history” and to list it among its top five public health priorities (Kolodny et al., 2015). The upsurge in opioid consumption has led to a sharp increase in ED room visits for nonmedical OPR abuse or misuse.

Similarly, the rate of individuals seeking for OPRs addiction treatment rose to 900%. Kolodny et al. (2015) noted that the association between opioid sales, opioid-related overdose mortality, and opioid addiction treatment has been well-established. Also, the researchers reported that people who use OPRs switched to illicit opioid (heroin), and 94% of those reported doing so because it is cheaper to obtain and difficult for them to access OPRs. Moreover, the prevalence of opioid addiction has increased significantly, and this has been found to be correlated with a sharp increase in heroin morbidity and mortality. Kolodny et al. (2015) noted that Whites aged 20-34 were more likely to be admitted to rehabilitation centers for addiction treatment, while heroin overdose mortality for Whites aged 18-44 has climbed to 171%.

In this article, Kolodny et al. (2015) aimed to describe the scope of OPRs use, the contributing risk factors and evaluate the role of addiction in aggravating the related mortality and morbidity. The strength of this study was that it recognized opioid dependence in medical and nonmedical users as the main driver of mortality and morbidity, contrary to the past where the focus has been made on medical users only. The weakness of the study is that the sample size and methods used to collect data were not described, which may affect its validity. This article seemed relevant because it focused on medical opioids as a public health concern and on its consequences (addiction and overdose mortality). However, it placed a special emphasis on heroin, aggravating the situation since it is cheaper to acquire by users. This study will expand knowledge by emphasizing on health insurance and relationship with treatment completion.

Meyer et al. (2014) described the medical and financial burden of opioid prescription abuse or misuse by examining 183 articles from the National Ambulatory Medical Care Survey (NAMCS). The research aimed to conduct a comprehensive review of the literature to further understand the medical and financial burden of opioid prescription abuse. The authors noted that the use of nonmedical opioid pain killers has been surging and has become a pressing public health concern in the U.S. The article reported that between 2002 and 2007, the rate of nonmedical rose from 11 million individuals to 12.5 million in the U.S. Meyer et al. (2014) also noted that the prevalence of people misusing opiates other than illicit drug (heroin) had surged dramatically from 1997 to 2007 with respectively 7 per 100,000 people to 36 per 100,000 people, accounting for 414% increase. The burden of opioid abuse has been growing, and Meyer et al. (2014) have estimated the opioid overdose-related mortality to range from 5,528 deaths in 2002 to 14,800 deaths in 2008. Other published articles have shown higher figures recently.

The article Meyer et al. (2014) also noted that the White House Budget Office estimated the medical expenditure for drug abuse to reach $300 billion annually. And in 2007, the estimated costs for misusing opioid were predicted at $55.7 billion (Meyer et al., 2014). But the article by Florence et al. (2016) estimated the global financial burden for opioid abuse prescription and addiction at $78.5 billion. Meyer et al. (2014) found non-opioid pain killing substances stayed steady between 26%–29%, but the proportion of opioid prescriptions has jumped considerably from 11% in the year of 2000 to 20 % in 2010. The outcomes showed that patients ‘prescription increases with age, accounting for 11.7% for 10–29 years old and 45.7% for 40–59 years of age. A strength of the study is that it provides insights for clinical implications to target those most affected. A limitation is that investigators found it difficult to differentiate abuse from misuse and diversion, which may misguide policymakers in their decision. The current study will further assess the relationship between sociodemographic factors, health insurance coverage, and treatment completion.

In a sudden twist of the situation, Morales et al. (2019) noted that fentanyl mortality from fentanyl-linked fatalities has become the main cause of deaths among U.S citizens. The article noted that drug abuse fatality in the United States reached a staggering number of 70,237 in 2017, accounting for 9% increase compared to the previous year. The paper noted that a new form of deadly opioid is now taking place, synthetic drugs such as illicitly manufactured fentanyl (IMF) and its equivalents. Morales et al. (2019) reported a sharp increase of IMF-related mortality from 3,105 in 2013 to 20,145 deaths (649%) in 2016. The article reported the distribution of IMF deaths in 2016 in Baltimore (Maryland), Providence (Rhode Island), and Boston (Massachusetts) to be 80.6%, 32.5%, and 35.3%, respectively.

This cross-sectional design by Morales et. (2019) used a sample of 308 participants who have a history of heroin or opioid use within the last six (6) months. The outcomes of the study showed that willingness for using illegal nonmedical fentanyl have been reported in 27%. It found that people commencing opioid use without prescription opioid drugs have the likelihood to prefer fentanyl and 2/3 of the respondents reported an opioid overdose in the past year. The study found an association between fentanyl and sociodemographic factors like race and ethnicity (Morales et al., 2019). The findings of the study could provide clinical implication like screening for fentanyl presence. The limitation of the study is that it could be misleading because of social desirability bias.

Ray et al. (2017) specifically examined opioid-related overdose trends in Indiana. The study assessed whether they are associated with variations in synthetic opioid medications. The authors used data from Marion County Coroner’s Office (MCCO), the Indiana Scheduled Prescription Electronic Collection and Tracking Program (INSPECT), the Marion County Forensic Services Agency (MCFSA), and records from the

Indianapolis Metropolitan Police Department (IMPD). The paper reported the prevalence of Indiana’s overdose fatalities to be 14.4 per 100,000 residents, ranking the state number 17th nationwide (Ray et al., 2017).

The toxicology test revealed that heroin, morphine, codeine, oxycodone, hydrocodone, oxymorphone, hydromorphone, and fentanyl were found to be the most common drugs used. Although hydrocodone and oxycodone remained the most prescribed opiates in Indiana, the study noted that heroin and fentanyl contributed mostly to the increase in overdose fatalities. But the National Institute on Drug Abuse reported that the age-adjusted rate of drug overdose has increased significantly in Indiana from 2016 to 2017 with 24.0 deaths per 100,000 in 2016 to 29.4 deaths per 100,000 in 2017.

Findings Ray et al. (2017) revealed that individuals aged 30-39 and 19-29 years old have the greatest mortality rate, with 26.6 % and 25.4%, respectively. The results also found a high proportion rate for male sex (66.7%), White ethnic group (85.3%), and never married or single (44.8%) [Ray et al., 2017]. A strength of this study is that it shows that Indiana State has fewer opioid treatment programs or OPTs (14) compared to other neighboring states like Illinois, Ohio, and Michigan. So, it provides insights for policy recommendations, including funding, and the creation of additional OPTs to avoid individuals from traveling a long distance to seek treatment. The study limitation was the researchers’ reliance on data, which may not be available sometimes as it has been the case for MCCO data.

In another research by Lowder et al. (2018), the inquirers sought to demonstrate the severity of undercounting opioid-related overdose fatalities in Indiana. Data suggested that Indiana is ranked 17th nationwide when it comes to opioid fatalities. Opioid overdose mortality in the United States has been well-established. Despite that, a significant number remained unspecified (Lowder et al., 2018). The study analyzed toxicology data in MCCO from 2011 to 2016 and examined a sample of 1,238 accidental poisoning deaths.

The outcomes of the study revealed that 57.7% of accidental overdose deaths were undetermined and opioids played a role in 34.2%. The results of the investigation showed that 86.8% of the cases were confirmed positive for opioid. Further, findings showed opioid-related deaths has doubled from 32.4% to 86.0% (Lowder et al., 2018). Strikingly, the outcomes demonstrated that fentanyl-related overdose went from 5.4% in 2011 to 51.5%, accounting for 853.7% increase (Lowder et al., 2018). However, 90% of the overall result involved opioid. Despite the massive spending by federal, state, and local government to curb the opioid epidemic, the failure to accurately evaluate fatal opioid-involved overdoses affects the effectiveness of the intervention strategies intended to address the issue (Lowder et al., 2018). One of the public health recommendations of the study was the improvement of local surveillance aiming at tackling the epidemic of opioid. As described by the previous survey, the reliance on population-level data to predict trends may lead to ecological fallacies (Lowder et al., 2018 and Ray et al., 2017).

Many studies have focused on the relationship between sociodemographic factors and substance abuse (Lamptey (2005); Ranjan et al., 2010 and Simoni-Wastila & Strickler (2011)). Little is known about their association with successful treatment completion. Also, there is limited literature about the association between health insurance coverage and successful treatment completion. This cross-sectional and secondary data analysis will expand knowledge by assessing the association between sociodemographic factors, health insurance coverage, and treatment completion outcomes for individuals abusing opioids.

Sociodemographic Characteristics and Opioid Abuse

The threat of substance abuse is a socially unacceptable truth, but it is also a disorder and has emerged as one of the top public health challenges of the new century. Globally, there is a growing trend in the number of individuals using substance abuse. This global issue of substance abuse has been influenced by social, economic, political, and psychosocial factors. The issue of drug abuse has contributed to rising tensions among societies (Rather et al., 2013). To understand this social phenomenon, Rather et al. (2013) investigates sociodemographic, and patients profile attending the drug rehabilitation unit.

In the study by Rather et al. (2013), the authors conducted a descriptive study using the Drug De-addiction Centre (DDC) at the local Police Hospital of Srinagar. A total of 198 patients were interviewed (Rather et al., 2013). The study results found that for those who abuse the drug, the mean age was 26.8 years, and 56% of respondents belong to lower-middle class. Poly-substance abuse was noted in 91.9%, and that medicinal opioids and cannabis were the most widely used substances abuse. Also, 76.8% of individuals started the initiation between 11 to 20 years old. Findings revealed peer pressure and experiencing psychological distress were key drivers for drug use. The study also noted the prevalence of a co-morbid psychiatric disorder to be high (Rather et al., 2013).

The study by Ranjan et al. (2010) also reported that substances abuse is a global problem, but it recognized that societies used it for relieving pain and for pleasurable sensations. Using a cross-sectional design, Ranjan et al. (2010) examined sociodemographic factors that contribute to drug abuse among respondents aged 15 and above. Researchers applied a two-stage sampling method to collect data in Malvani location (India), and four areas were selected including MHB Colony (2728 houses), NCC Colony (12420 houses), Akashwani Area (5443 houses), and Ambujwadi (3000 houses). Findings suggested that nearly 50 % tested positive for any single or multiple drug abuse habit. Participants aged 15-34 accounted for 59.8% of drug abusers. These outcomes were consistent with the previous study conducted by Gomes et al. (2018). For illiterate or primary or middle school levels, 72.1% of drug abusers were reported. The results also showed that 24.7% of drug abusers were illiterate compared to 16.9 % in nonabusers' group. 53.1% represented the semiskilled workers, and 27.2% accounted for the unemployed group. 65.2% of men have initiated drug between the age of 15 and 24 years old, and 81% of them cited peer pressure as the main factor. In their conclusion, Ranjan et al. (2010) noted that early age, illiteracy, low working status, and poverty are key drivers for drug abuse and that peer pressure plays a key role in the initiation stage for any drug abuse, especially for males. In their discussion, Ranjan et al. (2010) recommended training for parents and teachers by health professionals to curb this problem. This article is relevant because it investigates sociodemographic factors contributing to drug abuse. The present study will go further to investigate the association between health insurance coverage and treatment completion.

Lamptey (2005) also investigated fifteen sociodemographic characteristics of abusers compared characteristics of non-substance abusers. Several studies demonstrated that drug abuse is a persistent issue among adolescents. Most of the substance abuse occurred between the mid-tens and mid-twenties (Gomes et al., 2018; Kolodny et al., 2015; McHugh et al.,2014 and Wisniewski et al., 2008). Similar trends are shown in Lamptey (2005). According to Lamptey (2005), the age range of 15-24 years reported the greatest substance abuse, representing 83% of the population of the abusers. The study used a privately specialized clinic in Ghana to compared eighty-seven abusers to the same number of non-abusers. Findings revealed that substance abuse in adolescent males was statistically significant with $p<0.05$. Substantial variations between males and females regarding drug abuse were reported with $p<0.05$. The results found 1/3 of abusers abandoned their education early at the secondary level with $p<0.05$. Furthermore, results from Lamptey (2005) revealed that over half of abusers' parents were divorced, separated, or never married. One final note was that the perception of parents 'attitudes and perception of siblings did not play a role in shaping responders' way to abuse drug (Lamptey, 2005). Intervention plans targeting the above sociodemographic factors could ameliorate the rate of substance abuse and improve the overall health of the population. The article mentioned affordability as a limitation to the study because only those who can afford to visit the clinic are included. This study focused only on sociodemogarphic factors related to opioids abuse, but the current research will further investigate the correlation between insurance coverage and successful treatment completion.

In the survey by Simoni-Wastila & Strickler (2011), the researchers sought to approximate the frequency of prescription drugs problem and its associated risk factors. The survey applied data from the National Household Survey on Drug Abuse. A total of 4,049 respondents were included in the survey. Variables such as race, age, gender, marital status, urbanicity, education, work status, health insurance, income, and general health status were considered in the survey. Results found that 1.3 million individuals (15.5%) were considered as having an issue with a prescription drug. Having poor health, drinking alcohol, unmarried, having age of 35 and above, white race, and being female are predictors for prescription drug abuse. But full-time employment showed to have protective effects against the prescription drug problem. The strength of this study is that it was one of the first research emphasizing on the occurrence of issues related to prescription drugs and the underlying risk factors that are related to their use. This secondary data analysis will further explore the variables relationship with treatment completion for opioids abuse.

Moreover, Swendsen et al. (2009) studied the prospective associations between sociodemographic variables and drug addiction using data from the National Comorbidity Survey (NCS) and the NCS Follow-up survey. Similar to previous studies, this survey noted that the health effects of drug dependence (disorders) has been classified among the global public health urgencies. Many studies have demonstrated strong correlations between these disorders. Epidemiological studies have specifically found the prevalence of drug disorders to be linked to gender, younger age, lower education, unmarried status, low income, and other variables reflecting disadvantaged social status. This is consistent with the findings of many investigations (Lamptey (2005); Ranjan et al., 2010 and Simoni-Wastila & Strickler., 2011). This survey used a total sample of 5,001 participants from the National Comorbidity Survey (NCS) and the NCS Follow-up survey aged 15-24 years old, representing 87.6% baseline sample. Findings of the investigation revealed that many sociodemographic variables like in earlier studies are strongly correlated to drug addiction disorders like age, low education, ethnicity, and occupational. But, others like sex, residence, and number of children were not related (Swendsen et al., 2009). Swendsen et al. (2009) have practical recommendations targeting the most vulnerable populations. The study is significant for its emphasis on drug disorders and sociodemographic correlates. A strength of the study is its use of a large and nationally representative sample. The limitation of this survey is its assessment at baseline. This study will further explore the relationship between health insurance and treatment completion for opioids abuse.

Farhat et al. (2015) discussed specifically opioid dependence. The aim of the survey was to find out whether the sociodemographic profile is linked to the trend of opioid-dependence in patients at a treatment center in India. The survey noted that dependence to opioids contributed to high morbidity and mortality and can result in a high prevalence of psychiatric illnesses. A cross-sectional design has been performed at addiction rehabilitation Centre of Institute of Mental Health and Neurosciences. A total of 200 opioid subjects were recruited at the treatment center, and all of them fulfilling the

American Psychiatric Association's Diagnostic and Statistical Manual of Mental Disorders (Farhat et al., 2015). The conclusions of the survey suggested that being young was associated with opioid abuse. Prescription diversion was the main reason for drug abuse, and peer pressure was highly correlated with initiating substance or drug abuse. However, self-motivation was the key driver for seeking treatment (Farhat et al., 2015). The study proposed a multidisciplinary collaboration or approach to tackle illegal and non-authorized use of prescription opioid and bring the issue of drug abuse under control. The limitation of the study was that it used a smaller sample, which has the potential of affecting the validity and reliability of the overall outcomes.

Many cross-sectional studies have investigated sociodemographic factors with opioid abuse. A survey by Tavares et al. (2004) sampling 27,990 students aged 10-19 years old, found a linear correlation between social class, age, and opioid abuse. Results also found being divorced, unemployed, and place of residence to be strongly correlated with drug abuse. In similar trend, Henkel (2011) found that unemployment was not only associated with drug abuse it can also augment the risk of relapse after drug addiction treatment. But the study found the religious belief to be protective against drug use. Another survey by Gul & Sharma (2017) examined sociodemographic factors and trends of drug abuse among subjects at a rehabilitation center using a sample of 300 participants averaging 29.8 years old. The results of the study found opioids abuse to be prevalent in 179 (59.67%). Findings demonstrated that sociodemographic variables such as marital status (unmarried), low educational level, place of residence (rural), and low occupational level to be significantly correlated with drug abuse (Gul & Sharma, 2017). These findings are consistent with previous studies. The current investigation will learn more about the association between health insurance coverage and successful treatment completion.

Research Involving Drug Treatment

The opioid epidemic has become a public health crisis that affects people of all ages. Opioids are generally designed to relieve pain and can be very addictive. Licit substances (e.g., oxycodone, hydromorphone) and other illicit drugs like heroin are classified as opioids (Sanger et al., 2020). The use of opioid prescriptions can lead to opioids use disorder. Evidence suggested that in 2017, more than 2.1 million individuals suffered from an opioid use disorder because of prescription opioids abuse (Sanger et al., 2020). Opioid misuse has been increasing since 2000, and an estimated 586,000 people have been affected by a substance use disorder in the United States (Maglione et al., 2018). It has been reported that a high proportion of the population suffering from substance use disorder failed to enroll and receive adequate treatment services (Curtis, 2013). Also, the refusal for substance abusers to undergo treatment can potentially, among others, increase the prevalence in mortality, lead to loss of income, alter an individual's physical functioning, and bring up societal harm (Curtis, 2013). The need to treat substance disorder remains imperative, and a successful treatment completion can have positive outcomes and reduce treatment readmissions (Marie et al., 2015).

Further, Turan &Yargic (2012) identified various factors that influence treatment completion, including individuals' demographics, substance type and route of administration, the environment, and service settings or treatment program. But the authors recognized that successful substance treatment completion depends on individuals' acceptance to seek treatment and their level of engagement to stay the course (Turan &Yargic, 2012). Furthermore, it had been revealed that the completion of treatment for substance use disorder produces meaningful outcomes than hasty retreat or withdrawal from treatment programs (Curtis, 2013). While there is a pressing need to address prescription opioid abuse and its underlying health consequences, the correlation between health insurance coverage and treatment completion outcome has often been explored. This study will examine the health insurance coverage for opioid users in Indiana and their correlated successful treatment completion.

In a secondary data analysis, Marie et al. (2020) used the Treatment Episode Datasets-Discharge (TEDS-D) from the Substance Abuse and Mental Health Services Administration to examine the association between opioid admissions treatment referral source and successful treatment completions. The Treatment Episode Datasets-Discharge collects substance abuse data from funded public and private facilities in the United States and comprises about 1.5 million admissions annually (Marie et al., 2020). This study analyzed TEDS-D datasets from 2006-2010 using a large sample of $N = 2,909,884$ population. This study used a chi-square test and Logistic regression for data analysis. Statistical analysis of the sample showed that healthcare professionals' referrals with lower successful treatment completion rates compared to other referral sources [OR = 0.72, 95% CI 0.70 – 0.75; $p < 0.0001$]. Also, the results demonstrated that admissions for prescription opioids significantly lower treatment completion rates than other substances (Marie et al., 2020). These findings were significant because they might provide insight to target healthcare professionals to improve screening and referral to address the ongoing opioid crisis. Although the study assessed the correlation between treatment completion and referrals, it did not assess clients' health insurance coverage to see whether it plays a role in the treatment outcomes. This study intends to fill this gap.

In another research, Turan & Yargic (2012) assessed the association between sociodemographic factors, substance use, and criminal activities on successful treatment completion. A total sample of 115 subjects aged 18 and older participated in the survey. Participants in this study were individuals for substance abuse treatment follow-up who were on probation at the Istanbul Probation and Help Center in Turkey. The study aimed to examine treatment completion rates on substance abuse among individuals on probation, substance use characteristics, and criminal activities (Turan & Yargic, 2012). This study's primary dependent variable was treatment completion, and the independent variables (predictors) consisted of sociodemographic factors, substance use types, and criminal history. Chi-square test, Fisher's exact test, and logistic regression were performed to analyze data. The study found the treatment completion rate to be at 59.1%, while non-completers represented 40.9%. The overall results demonstrated that sociodemographic factors were not statistically significant contrary to previous studies. However, the findings revealed statistical significance between substance use types and criminal activities on treatment completion (Turan & Tragic, 2012). The study might have practical ramifications in designing intervention strategies to tackle the problem of substance abuse and improve treatment outcomes. Nonetheless, the inclusion of small sample size, fewer females (only five of them took part in the study), and the selection of individuals aged 18 and older constituted some of the limitations of the research and might affect the validity of the study. However, the study recommended further investigation be conducted that includes a larger sample with more females and adolescents for more meaningful outcomes. Overall, this study is significant because it explored the association between sociodemographic factors, substance use types, and treatment completion on substance abusers. The current secondary data analysis will explore further the impact of health insurance coverage on treatment completers.

Moreover, the study by Sanger et al. (2020) investigated the correlation between the source of first opioid exposure and treatment outcomes. The authors used a systematic review and meta-analysis to carry out their investigation. The database searches used included EMBASE, MEDLINE, PsycINFO, and CINAHL (Sanger et al., 2020). During the analysis, 27,345 articles had been examined; the investigators utilized five observational studies in their mixed-method analysis (qualitative and quantitative). The findings of this investigation revealed that individuals who were initially exposed to opioids via prescription had less likelihood of using illegal opioids while undergoing medication-assisted treatment than those exposed to recreational drugs. This systematic review analysis found that initial exposure to opioids via prescription or recreational means can impact treatment outcomes for opioid addiction (Sanger et al., 2020). Findings revealed that no significant relationship was found in treatment length between prescription opioid and recreational use initiation. The study suggested that increase prescription of opioids can contribute to a high prevalence of opioid use disorder. However, the implementation of a new approach can improve OUD's treatment outcomes (Sanger et al., 2020). The study's strength was its methodological nature, enabling the investigators to employ screening approaches that involve all studies. However, one of the study's limitations was the lack of adjusting for confounding variables, which might affect the validity of the outcomes. Another limitation was that only data from North America and Australia were analyzed, which might affect the generalization of the outcomes. This study seemed significant because it raised the public health concern of opioid prescription and its contribution to opioid use disorder while focusing on their influence related to treatment outcomes. The current secondary data analysis will look further to assess sociodemographic factors and the impact of health insurance on treatment completion rates.

Treatment for opioid addiction is important to improve the well-being of those affected. It has been well-documented that access to medications for opioid use disorder in residential addiction treatment facilities can be effective in individuals with such a problem (Huhn et al., 2020). Despite substance abuse treatment availability, many challenges still exist, including accessibility and lack of insurance coverage, among many others (Huhn et al., 2020). In a study conducted by Huhn et al. (2020), the investigators assessed the accessibility and application of MOUDs in residential addiction treatment facilities. The purpose of the study was to investigate whether there are differences between access to MOUDs and their use in residential treatment facilities. It also assessed the relationship between facility-level with access to MOUD and admissions-level. The inquirers applied a cross-sectional study design by examining large data surveys from the 2017 National Survey of Substance Abuse Treatment Services, 2017 Treatment Episode Data Set–Admissions and state-level opioid overdose mortality rates state-level Medicaid coverage (Huhn et al., 2020). Descriptive statistics and logistic regression were performed in this analysis. Findings revealed that individuals who were admitted for treatment were predominantly men (67 %%), White patients (74%), and those aged 25-54 (81%). The study results showed that only 1.3% of treatment facilities offered all MOUDs to those affected, and 60% did not. Also, residential facilities offering XR-NTX generated greater odds of offering both buprenorphine and methadone with [OR, 22.93; 95% CI, 17.95-29.28; $P < .001$] and [OR, 6.73; 95% CI, 3.33-13.62; $P < .001$], respectively. Most importantly, the study results suggested that individuals with opioid use disorder and seek treatment at residential facilities where the care was expected to be of quality failed to receive the care they needed (Huhn et al., 2020). One limitation was that facilities reporting for individuals receiving MOUDs might not be known, which might affect the study's generalizability. Overall, the study and its conclusions seemed significant. It called for the need to address the ongoing problem of the opioid epidemic in the United States while restricting access to those who need it. There is an existing belief that most patients do not access quality care because of a lack of health insurance coverage. The current secondary data analysis proposes investigating further and whether there is an association between health insurance and treatment completion for opioid users.

A survey by Brown (2010) examined predictors of substance abuse treatment completion in drug court. The survey's measured demographic profiles, socioeconomics, substance use, and criminal justice background of participants. The number of subjects included in the study was N=573. Bivariate and multivariate logistic regressions were performed to assess such associations (Brown, 2010). Bivariate logistic regression revealed that being unemployed, belonging to the non-whites race, and having the highest grade completed were among predictors of substance abuse treatment completion. Multivariate regression was performed and demonstrated that unemployment, lower educational attainment, and cocaine were correlated with failure to complete treatment. Similar outcomes were found by Knight et al. (2001). However, the use of administrative data and self-reporting were considered limitations of the study (Brown, 2010). However, Newton-Howes & Stanley (2015) rebutted the findings and found that primary, secondary, high school, and college levels compared to graduate-level were predictive of a greater likelihood of treatment completion. This study seemed significant to the current research because it assessed demographic factors that predict failure to substance abuse treatment.

Besides, Suntai et al. (2020) examined racial differences related to substance use treatment completion among older adults using a cross-sectional design. The study aimed to ascertain the extent of racial discrepancies regarding substance use treatment completion among older adults. The study analyzed the Treatment Episode Data from the Substance Abuse and Mental Health Services Administration (Suntai et al., 2020). Chi-square tests, bivariate, and multivariate logistic regression were utilized to analyze the data. Findings showed that Blacks were less likely to complete a substance use treatment program than Whites with OR = 0.630. Also, males were more likely to complete treatment than females with OR = 1.288. There no difference found in marital status. But the survey found that individuals not in the labor force had lower completion rates than those employed with OR = 0.799. Similar trends were found in the survey conducted by (Bazargan-Hejazi et al., 2016). This survey was meaningful because it assessed treatment completion predictors in outpatient, residential facilities and utilized a cross-sectional and secondary data analysis to report their findings.

Nonetheless, Guerrero et al. (2014) investigated gender discrepancies related to substance abuse treatment service use and outcomes within racial and ethnic groups. The survey used a prospective longitudinal design from the National Treatment Improvement Evaluation Study (NTIES) longitudinal in the United States. Descriptive statistics, chi-square, and analysis of variance were performed in this study. The study's findings revealed that women from all subgroups benefited from services and treatment outcomes compared to men (Guerrero et al., 2014). Besides, the study found that gender as a moderator in the analysis. However, it found that females were more likely to enter residential treatment facilities. There was no statistical difference between gender and treatment completion with (OR: 0.93, 95% CI: 0.86–1.00) [Bazargan-Hejazi et al., 2016]. Another survey also found no gender differences in substance abuse treatment (Brown, 2010). The current study will assess similar demographic characteristics and their association with treatment completion outcomes.

A study by Stahler & Mennis (2020) also examined to see if medications for opioids use disorder (MOUD) can lead to treatment completion and retention in short-term and long-term residential programs. The study used large datasets from the 2015–2017 TEDS-D (Treatment Episode Dataset-Discharge) for opioid using adults in residential treatment. Descriptive statistics, chi-square, bivariate logistic regression, and multiple logistic regressions were applied to carry out the analysis. Findings of the study showed that in short-term residential treatment, MOUD was associated with a greater likelihood of treatment completion (OR = 1.404) and increased retention rate (OR = 1.337) [Stahler & Mennis, 2020]. However, in long-term residential treatment programs, MOUD was less likely to complete treatment (OR = 0.743) and found no difference in retention (Stahler & Mennis, 2020). The significance of this study was that it evaluated predictors for short-term and long-term residential treatment completion and retention, part of the purpose of the current. However, it failed to report the association between participants' sociodemographic characteristics and short-term and long-term residential treatment completion and retention outcomes.

Health Insurance Coverage and Substance Abuse Treatment

Opioid abuse has been affecting Americans from every age group. Studies suggested that many individuals have died from opioid abuse or opioid-related substance. In 2018, the CDC reported three quarters (70%) of total deaths in the United States attributed to opioids (CDC, 2020). Data revealed that licit prescriptions of opioids and street opioids play a significant role in this skyrocketing death rate. The good news is that treatment exists in tackling substance abuse in general and, specifically, opioids abuse. Huhn et al. (2020) recommended that the residential treatment facility setting seemed to be the most effective treatment-level for dealing with this public health issue. However, many barriers might impede the successful completion of treatment, including health insurance coverage and access to services utilization. Implementing evidence-based substance use treatment by increasing service utilization can reduce mortality and morbidity due to substance abuse (Feder et al., 2019). It had been shown that only 10% of those affected by substance use disorder could access treatment (Feder et al., 2019). The reason for that was the lack of health insurance coverage that refrained people from seeking treatment for opioid use disorder. People with low socioeconomic status were more vulnerable. The relationship of health insurance coverage with opioid abuse and access to treatment services has often been explored, and this study intended to do so.

In the article by Feder et al. (2019), the researchers sought to understand the impact of health insurance on individuals using injectable drugs. Using the AIDS Linked to the Intravenous Experience (ALIVE) data, the investigators extracted a sample size of 1724 adult participants who reside across the Baltimore area in Maryland. Among variables assessed by the researchers included dependent variables (Receipt of specialty substance use treatment, Receipt of buprenorphine, and having a usual source of medical care) and the independent or predictor variable of self-reported health insurance status (Feder et al., 2019). Data were analyzed using descriptive statistics and logistic regression models. The results showed the participants' mean age to be 51, and 30 percent of them were HIV tested positive. Also, males have a higher frequency of visits (2/3), while 90% of participants were African Americans. The most striking outcomes exhibited a statistically significant correlation between insurance type use and treatment receive with $z = 2.7$ and $p < .01$. Findings revealed that having health insurance coverage had greater odds (3 times) of getting buprenorphine treatment than those who lacked insurance.

Furthermore, it showed that having insurance was strongly correlated with higher medical care use (Feder et al., 2019). Finally, it demonstrated that holding health insurance can be associated with the use of specialty substance use treatment (OR 2.0, 95% CI 1.6 to 2.5). The findings were significant because it might enable to design interventions that expand health insurance to those uninsured. However, the study had some limitations. The study was able to assess only treatment to buprenorphine. But the study had not assessed Methadone and Naltrexone treatments and their association with having insurance. Also, the study could not control for all confounding factors, and the sample size was predominantly African American, which might affect the generalizability of the outcomes. The current secondary data analysis will assess whether acquiring health insurance predicts treatment completion outcomes for opioid users.

Another article by Cummings et al. (2014) discussed private health insurance coverage and specialty treatment admissions for substance abuse disorder. The survey aimed to assess the association between private health insurance and the receipt of treatment for specialty substance use disorder. The study compared the receipt of specialty for substance abuse treatment between uninsured and individuals having private insurance. Data from the National Survey of Drug Use and Health or NSDUH using a cross-sectional design. A large sample of 177,462 people aged 18 to 64 participated in the survey (Cummings et al., 2014). Among the variables of interest assessed were receipt of specialty treatment for substance abuse (inpatients and outpatients) from rehabilitation centers (dependent variable) and health insurance coverage on categorical level (Cummings et al., 2014). Also, sociodemographic characteristics were evaluated, including gender, marital status, age, race/ethnicity, employment status, income level (Cummings et al., 2014). Findings revealed that private insurance was significantly correlated with the increased use of any specialty substance use disorder care for individuals experiencing alcohol addiction with a p-value <0.05 (Cummings et al., 2014). Logistic regressions were performed to establish an association between the dependent and independent variables. Cummings et al. (2014) further reported that cost and lack of health insurance coverage were among the main problems' individuals face for substance abuse treatment. In another survey regarding the lack of insurance coverage in workers, the outcomes demonstrated that uninsured workers have a higher likelihood of using alcohol and other illicit drugs than those who were insured. It further showed uninsured workers lacked drug assistance programs known as EPAs by employers than insured workers (Miller et la., 2007). However, Cummings et al. (2014) suggested that the recent enactment of the Mental Health Parity and Addiction Equity Act (MHPAEA) in 2008 and the Affordable Care Act (ACA) of 2010 were both designed to expand health insurance coverage for substance use disorders to improve treatment outcomes. Although Cummings et al. (2014) did not say whether an association existed between the selected sociodemographic profiles, a survey by Allcock et al. (2019) found a marked correlation between health insurance coverage and gender, education, and income. The current study will expand further in assessing such association.

A study by Mojtabai et al. (2020) investigated private health insurance use with substance disorder treatment. In contrast with Cummings et al. (2014) findings, the survey by Mojtabai et al. (2020) examined sociodemographic factors and found that having coverage was statistically significantly associated with receiving treatment with [OR = 2.09, 95% CI = 1.61–2.72, $p < .001$]. Also, the results from Mojtabai et al. (2020) found that participants with coverage were older than those lacking coverage (60.8% vs. 43.7%). Those with having coverage tend to be more educated than those without coverage (58.7% vs. 50.4% had any college education, $p < .001$) and gained significant family income than those without coverage (77.7% vs. 61.6%) [Mojtabai et al., 2020]. Further, Allcock et al. (2019) assessed sociodemographic patterns associated with health insurance in Namibia using a large sample of 14,443 aged 15 to 64 years. The survey applied multivariable mixed-effects Poisson regression analyses. The results of the study by Allcock et al. (2019) demonstrated that health insurance was associated with health service utilization and was independently associated with sex, education, and wealth. These findings were significant. The current study will further investigate the association between sociodemographic factors and treatment completion for opioids abusers and the association between health insurance and treatment completion.

Another study by Olfson et al. (2018) assessed variations in private insurance coverage and behavioral treatment for individuals aged 19 to 35 years after implementing the Affordable Care Act on provisions of insurance coverage. The researchers applied a cross-sectional design and extracted from the 2008 to 2016 National Surveys on Drug Use and Health (NSDUH). The survey measured Health insurance coverage type and treatment for substance use disorders. Additionally, the survey assessed sociodemographic variables, including income, marital status, student status, and employment. Structured interviews were used in evaluating substance use disorders and mental health issues by applying the *Diagnostic and Statistical Manual of Mental Disorders, Fourth Edition (DSM-IV*) [Olfson et al., 2018). Findings of the survey revealed a significantly more significant increase in private insurance for individuals aged 19 to 25 years compared to 26 to 35 years with (7.7 % points; $P < .001$) and (1.2 % points; $P = .02$), respectively (Olfson et al., 2018). Also, the study results found among patients with selected substance use disorders, there was a significantly greater coverage increase for individuals aged 18 to 25 years than for 26 to 35 years (9.0% points; 95% CI = 5.5%, 12.5%). It found that the younger age group with substance use disorders had significant gains in coverage (Olfson et al., 2018).

Treatment Options for Opioid Abuse

Despite the devastating health consequences of opioids abuse, there are various treatments available for opioid dependence or abuse (Stotts et al., 2009). However, Cummings et al. (2014) suggested that many individuals with substance abuse or drug problems cannot access care because of lack of health insurance and the high costs of service provided. Stotts et al. (2009) identified two ways for treating opioids dependence, including opioid maintenance treatment and detoxification, and in many cases, patients utilize both. The most recommended medications for opioid addiction include agonists, partial agonists, and antagonists (Stotts et al., 2009). Agonist and partial agonist medications are administered for maintenance and detoxification. The antagonist is used to enhance outcomes (Stotts et al., 2009). The most common agonist medication used for opioid maintenance and detoxification is Methadone. Buprenorphine is a partial agonist for opioid dependence. Naltrexone is administered as an opioid dependence antagonist (Stotts et al., 2009).

-Methadone: Methadone is used for replacement therapy for heroin and other opiates dependence. A dose ranging from 80 – 150 mg is recommended with 20-30 mg starting daily dose. The dose is increased by 5 or 10 mg gradually until the maximum dose is attained (Stotts et al., 2009). Methadone maintenance treatment or MMT has shown to be effective in improving treatment retention and outcomes and lowering mortality rates (Stotts et al., 2009). However, there is growing evidence that Methadone can increase relapse for opioid dependence (Stotts et al., 2009). The use of methadone is known to be correlated with cardiac effects (Stotts et al., 2009).

-Buprenorphine: Is used as a partial agonist to control opioid withdrawal symptoms. The recommended oral for Buprenorphine oral is 24 or 32 mg. Partial agonist use has decreased the risk of overdose and improved treatment retention outcomes (Stotts et al., 2009). But Stotts et al. (2009) suggested that partial agonist might have the ability to reduce Buprenorphine optimal efficacy.

-Naltrexone: Naltrexone is administered orally and is known as a long-acting opioid antagonist that has proven effective for preventing relapse of alcohol and opioid dependence (Stotts et al., 2009). Fifty (50) mg of naltrexone is recommended. Higher doses of naltrexone are sometimes administered for a longer duration of action (Stotts et al., 2009). However, patients who use naltrexone can experience some side effects such as headache, nausea, abdominal pain, dysphoria, and depression (Stotts et al., 2009).

These literatures were selected because they assessed key variables in this analysis (independent and dependent variables).

Existing Policies for Opioid Abuse

Many public health initiatives have been implemented to tackle the growing problems of higher prevalence of opioid prescription misuse nationwide and across local jurisdictions. In 2006, CDC had undertaken robust efforts to track better and understand data related to the opioid overdose epidemic. In that optic, CDC has crafted five (5) strategies designed to prevent opioid abuse, overdose, and deaths. Monitoring cases of abuse using surveillance and research, involving tribal leaders, local and State jurisdictions, providers, and payers are among the initiatives. CDC also was committed to empowering consumers to make choices and to partner with public safety (CDC, 2019). Many studies have also proposed and implemented treatment and preventive measures related to opioid abuse. Treatment measures such as the creation of de-addiction centers have been used to help those who are suffering from opioid use disorder (Farhat et al., 2015; Heydari et al., 2014 and Tetrault and Butner ., 2015). Other studies focused on education-based interventions to help them abandon opioid prescription abuse (Morales et al., 2019; Tetrault and Butner (2015); and Tze et al., 2012).

One of the important initiatives implemented in Indiana State to curb the opioid crisis is the NextLevel Recovery Indiana. The initiative focuses on prevention, treatment, enforcement, and training for healthcare professionals. The NextLevel Recovery Indiana provides access to resources, emergency personnel, community leaders, and supports to individuals with opioid use disorder and their families (Indiana State Department of

Health, 2019). Indiana state applies the Indiana Scheduled Prescription Electronic Collection and Tracking (INSPECT) surveillance system to track down and address prescription drug abuse and diversion (ISDH, n.d).

Summary

The prevalence of prescription drug abuse increased significantly and faster in recent years in the United States. Opioids remained the most widely abused prescription drugs and show to contribute to the worsening of the epidemic. Many studies and literature reviews recognized opioid abuse as the most pressing challenge in the public health field. They also demonstrated the need to address such a growing public health problem. Several studies showed that opioid abuse led to high mortality and morbidity rate (Gomes et al., 2018; Meyers et al., 2014; and Morales et al., 2019).

Various studies investigated sociodemographic factors with opioid abuse. Findings from these studies demonstrated a marked association between sociodemographic profiles and prescription opioid abuse. The outcomes noted that sociodemographic factors like race, sex, single, younger age, residence, and unemployment are strongly correlated with prescription drug abuse (Lamptey (2005); Ranjan et al., 2010 and Simoni-Wastila & Strickler (2011)). But other studies found few sociodemographic factors were not related to opioid abuse. Nevertheless, the association between sociodemographic factors for opioid abuse and their relationship with treatment completion had been assessed. It had been shown that sociodemographic factors are significantly correlated to opioid abuse treatment completion. But other studies disputed such findings. Additional studies evaluated the association between insurance coverage types and specialty treatment for substance use disorder, more specifically with alcohol, and found that individuals with coverage have better access to treatment. Others disputed such a claim. The implementation of recent regulations in 2008 and 2010, such as MHPAEA of the ACA, respectively by congress, has led to the expansion of coverage for substance use disorder. The current quantitative cross-sectional research will further assess the association between sociodemographic attributes, health insurance coverage, and treatment completion for opioids abuse in Indiana. Despite high expenditure for substance use and opioid abuse, but the crisis continues to grow. This literature review offered the necessary tool for the research method (chapter 3), which incorporates the research questions and the design format to carry out this study. The research method section will discuss the recruitment of subjects, sampling method used, collection of data, ethical procedures, and threats to validity.

Chapter 3: Research Method

Introduction

This cross-sectional and quantitative research design sought to investigate the association between sociodemographic factors and treatment completion for opioid abusers in Indiana. The study also sought to examine the association between health insurance coverage and treatment completion for opioid abusers in Indiana. The completion of this study will provide another perspective for improving the treatment and retention for opioid abusers in Indiana, including for individuals having a problem accessing care because of a lack of health coverage. Further, the outcomes of this study would help expand insurance coverage and improve access to care. This cross-sectional and quantitative research was guided by the questions below:

1. Is there any association between sociodemographic factors and treatment completion for opioid abusers among residents in Indiana?

2. Is there any association between health insurance coverage and treatment completion for opioid abusers in Indiana?

3. Is there any association between health insurance coverage and treatment completion for opioid abusers in Indiana after controlling for sociodemographic factors?

This chapter will discuss the study's research design and its rationale and the detailed research methodology, including the population study, sample size, sampling procedures, and data collection. Besides, the chapter will describe the instrumentation and operationalization, the data analysis plan, and threats to validity of the study. Finally, an overview of the ethical research procedures and a summary were presented.

Research Design and Rationale

I will use the 2017 Treatment Episode Data Set Discharges (TEDS-D) from the Substance Abuse and Mental Health Services Administration (SAMHSA), a branch of the U.S. Department of Health and Human Services. A quantitative cross-sectional study design was applied. The data used were deidentified and were publicly accessible. Indiana data were extracted from the datasets for this analysis. This study sought to evaluate the association between sociodemographic factors, substance abuse (opioid only reported at admission), and treatment completion for opioid abusers. Besides, the extent of the relationship with treatment completion will be assessed when controlling for the selected sociodemographic factors. There is limited literature on health insurance coverage on treatment completion. This study will fill the gap by examining the association between health insurance coverage for treatment and successful treatment completion for opioid abusers at discharge.

Dependent and Independent Variables

The primary dependent variable (DV) considered in this study was successful treatment completion status at discharge. Treatment completion in this dataset was defined as "all parts of treatment plan or program were completed" (TEDS-D, 2017). This secondary data analysis will apply this definition concept. The outcome variable of treatment completion was measured on a categorical level. Therefore, the researcher used the variable successful treatment completion as "Treatment completed" or "Treatment not completed" for any reasons such as "dropped out of treatment, terminated by the facility, transferred to another treatment program or facility, incarcerated, death, and other."

Another outcome variable involved in this research was opioid abuse (opiates/synthetics abuse) for individuals using opioids as their primary substance use.

The independent variables (IV) in this study included sociodemographic attributes (education, gender, age, race, marital status, and employment) and health insurance coverage at admission. The independent variables predict or forecast the values of the dependent variable in the model (Statistics Solutions, 2019). In a research study, the independent variable is tested to determine its relationship regarding an observed phenomenon *(*Siegle, n.d).The selected sociodemographic attributes were measured as categorical. Opiates/synthetics represented the substance reported at admission. Opiates/synthetics were considered in this study as any substance use containing opioid and drug morphine-like effects that individuals reported at admissions as their primary substance use (TEDS-D, 2017). It included buprenorphine, codeine, hydrocodone, hydrocodone, hydromorphine, meperidine, morphine, opium, oxycodone, pentazocine, tramadol) [TEDS-D, 2017]. In this study, opiates/synthetics were measured as a categorical variable. Finally, health insurance coverage was measured as dichotomous (insured versus uninsured).

The research method best suited was cross-sectional and quantitative research design. The rationale for choosing a cross-sectional study approach allows evaluating whether there is a correlation between exposures (IV) and outcomes (DV) variables at one time (Setia, 2016). Another justification for this study was the availability and accuracy of the dataset, and it was inexpensive and timesaving. A cross-sectional design is the most convenient for public health planning, monitoring, and evaluation (Setia, 2016).

This study examined the correlation between sociodemographic factors (education status, gender, age, race, marital status, and employment status) and opioid abusers in Indiana. Additionally, the current research analyzed the association between health insurance coverage at admission and treatment completion status for opioid abusers in Indiana. The analysis of data was performed using SPSS. The researcher will run descriptive statistics to display data summary. Also, Chi-square and logistic regression were performed. The outcomes would enable identifying specific sociodemographic attributes and health insurance coverage that predict successful treatment completion status for opioid abusers in Indiana. Understanding these factors could help promote positive social change by implementing policies that expand health insurance coverage and improve treatment outcomes for opioids abuse in Indiana. This may improve morbidity and mortality rates related to opioid abuse and overdoses in Indiana.

Much research had been conducted to explore sociodemographic factors with opioids abuse but limited research on the association between health insurance coverage and successful treatment completion. This research was intended to fill that gap. Understanding the relationship between health insurance coverage and successful completion of opioid abuse treatment is essential in the public health field. There is a common belief that substance abusers having a government type of insurance or not having insurance were more likely to be rejected for substance abuse treatment.

When completed, this study could design policies to expand health insurance coverage for individuals dealing with substance abuse problems at the state and local levels. Investigating the association between the selected sociodemographic factors, health insurance coverage, and treatment completion for opioid abusers may help promote positive social change. The study could help expand insurance coverage for substance abusers, including opioid abusers and underserved individuals. This study's findings would improve treatment outcomes and reduce morbidity and mortality due to opioid abuse among Indiana residents.

Methodology

Population

Background of Indiana population characteristics

The state of Indiana is in the Midwest region of the United States. It is one of the largest and most populated states ranking 38th and 17th, respectively. Indianapolis is the capital and the largest city in the state. There are 92 counties in Indiana, and Marion County, where Indianapolis seats, is the largest and most populated counties in Indiana. According to the United States Census Bureau (2019), the population of Indiana was estimated at 6,732,219 residents as of 2019. The racial distribution of the population includes Whites (84.8%), Blacks (9.9%), Latinos (7.3%), Asians (3%), and the rest represent Native Americans (U.S. Census Bureau, 2019). The population is composed of 50.7% females and 49.3% males. The percentage of individuals earning high school degrees or higher is 88.6% and those with a bachelor’s or higher represents 25.9% (U.S. Census Bureau, 2019). The state median household income was $55,725. Employed individuals were estimated at 3,275,056 while unemployed represented 112,310, and the state unemployment rate stands at 3.3% (U.S. Census Bureau, 2018). The mean age was estimated at 37.9.

The 2019 U.S. Census Bureau reported the preschool population in Indiana aged 0 to 4 to be 418,340. This number represents 6.2 percent of the general population estimates. The school-age (5 to 17 years old) was 1,149,634 people, accounting for 17.1 percent. Estimates showed the population of individuals having college-age (between 18 and 24 years old) to be 659,745. This figure represents 9.8 percent of the total population. Additionally, younger adults aged 25-44 account for 1,719,646 people, representing 25.5 % of the general population (U.S. Census Bureau, 2018). Furthermore, the same data revealed the population of older adults between 45 and 64 years old to be 1,699,111people, accounting for 25.2 percent of Marion County population. Finally, the population of individuals aged 65 and more was estimated at 1,085,743 people (16.1%) [U.S. Census Bureau, 2018]. The above age distribution of the population showed individuals aged 25-44 to be the greatest (25.5%), followed by older adults or 45-64 (23.7 %), school-age (17.1%), older people (16.1%), College-age (9.8%), and preschool (6.2%) [U.S. Census Bureau, 2018.] Knowing these demographic characteristics of Indiana is of paramount importance for undertaking this cross-sectional design study.

Target Population

I used the 2017 TEDS-D dataset to conduct this analysis. The Treatment Episode Data Set Discharges or TEDS-D represents annual discharges from substance abuse treatment facilities (TEDS-D, 2017). The dataset used does not record all admissions or discharges but report admissions to accredited treatment facilities for substance abuse that receive local and federal funding. TEDS-D recorded information for individuals aged 12 and older (TEDS-D, 2017).

The current cross-sectional, quantitative research approach was applied to address the severe problem of opioid abuse and overdoses that Indiana faced. McLeod (2014) defined a target population as the entire group of subjects or individuals to which investigators are interested in generalizing the outcomes. The target population involves specific characteristics and is the group from which the sample may be drawn (McLeod, 2014). Evidence suggested that opioid abuse in the U.S affected **y**ounger people aged 24-45 more than any other age group (Gomes et al., 2018). The attributable opioid-related mortality was highest among adults aged 25-34- and 35-44-years. A similar trend was seen in Indiana, and data showed that individuals aged 18 to 25 years old were more vulnerable than other groups (NIDA, 2018). It had been shown that individuals aged 18 and older are predominantly the most affected by opioid abuse in Indiana and this cross-sectional study was going to focus on this age group. It was expected to see the target population to reach many thousand in Indiana.

Sampling and Sampling Procedures

Sampling Strategy

The present cross-sectional study sought to evaluate the relationship between some sociodemographic attributes and successful treatment completion for opioid abusers in Indiana. Sociodemographic factors were adjusted to evaluation their relationship with abusers’ treatment completion. It further assesses the correlation between health insurance coverage and treatment completion for opioid abusers in Indiana. A simple random sampling strategy was applied in this cross-sectional study. This type of sampling seemed the most appropriate because of its tendency to use a probabilistic approach where subjects have an equal chance of being selected, and the drawn sample is more representative of the target population (Elfil & Negida, 2017).

Inclusion of participants comprised of the selected sociodemographic characteristics (age, gender, race, education, employment status, and marital status), opioids abuse reported at admissions as primary substance (other opiates/synthetic abuse), completion of treatment at discharge, health insurance status, and being 18 and older. Exclusion criteria included participants less than 18 years and all missing cases following the missing at random (MAR) procedure. I used any precautionary measures to ensure accuracy of data being analyzed.

Sampling Procedures

The sample size for this cross-sectional design study was determined by using the power calculator, G*Power 3.1.9.7. The use of G*Power in this research helps to determine an *a priori* practical compromise sample size. G*Power is a stand-alone, very useful power analysis program for conducting various statistical assessments that are frequently used in the social, behavioral, and biomedical sciences (Faul et al., 2009). For the determination of sample size, it is essential to apply statistical power, which can help the researcher to avoid type I and type II errors (Faul et al., 2009).

In this analysis, the parameters for calculating sample size were set on Z-Tests since a probabilistic approach was applied, and logistic regression analysis was selected as the statistical test to be conducted. In addition, the medium effect size was set to be a choice because setting the “a priori” effect size level that is too high or too low has the potential of increasing the risk for error (Sullivan, 2012). Setting the effect size is indispensable because, as stated by Sullivan (2012), it is the main finding of a quantitative study. Further, a p-value can tell the reader about the real effect, but the p-value cannot estimate the effect (Sullivan, 2012). We set an acceptable coefficient of determination (effect size), also known as R square to be 0, representing a measure of the proportion of variance between the variables and can vary from 0 to 1. Using the G*Power with a confidence interval of 5 % and considering a power of 0.95, the generated sample size for achieving empirical validity with two or more predictors was estimated to be 988 participants. However, to ensure greater power, I used the entire sample contained in Indiana datasets.

Table 1

Protocol of Power Analysis

z tests - Logistic Regression

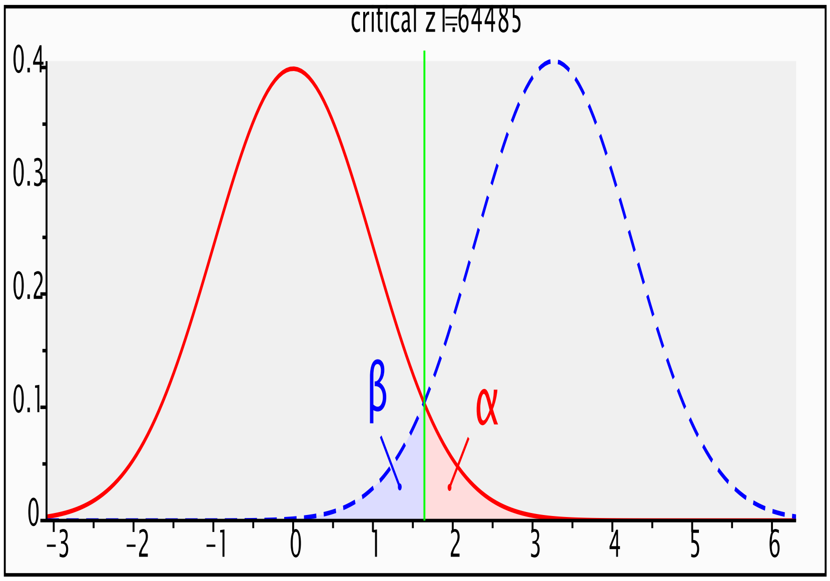
Options:	Large sample z-Test, Demidenko (2007) with var corr		
Analysis:	A priori: Compute required sample size		
Input:	Tail(s)	=	One
	Odds ratio	=	1.3
	Pr(Y=1|X=1) H0	=	0.2
	α err prob	=	0.05
	Power (1-β err prob)	=	0.95
	R^2 other X	=	0
	X distribution	=	Normal
	X parm μ	=	0
	X parm σ	=	1
Output:	Critical z	=	1.6448536
	Total sample size	=	988
	Actual power	=	0.9501283

Z Tests: Protocol of power analysis for the determination of sample size and interactions

Analysis: A priori: Compute required sample size

Figure 1

G Power Analysis for the Required Sample*



Data Collection

Participants can be accessed through the 2017 TEDS-D archival data managed by the Substance Abuse Mental Health Services Administration (SAMHSA). TEDS-D data gathered information on individuals’ demographics, their substance abuse pattern, and their admissions and treatment outcomes at discharges from all facilities receiving public funds. The data collected in the 2017-TEDS-D concerned individuals aged 12 and older, and the information reported from 46 states and the District of Columbia. The TEDS is composed of two major components, including admissions and discharges (SAMHSA, 2019).

Indiana data was extracted from the TEDS-D datasets, and participants in this study were individuals who reported abusing opioids as their primary substance use. The information gathered to be examined would include participants' sociodemographics (age, gender, race, educational level, employment status, and marital status), health insurance coverage status, reported opioid abuse at admissions and completed treatment at discharge. However, we estimated the sample size to be 988 participants using G*Power tools. The population of individuals undergoing substance abuse treatment in Indiana was estimated to be 21,000 people (SAMHSA, 2019).The collected data in the TEDS-D were publicly available and de-identified. The material contained in the TEDS-D document is presented in the public domain and does not require permission to be accessible (SAMHSA, 2019). Data were accessible on Substance Abuse and Mental Health Data Archive (SAMHDA) through CDC WONDER. Because TEDS-D was the most trusted data sources for substance abuse and mental health, it is generally accepted as reliable.

Instrumentation and Operationalization

Instrumentation

The survey instrument tool applied in this cross-sectional study to collect information from participants was the Treatment Episode Data Set – Discharges (TEDS-D) of 2017. Reported data concerned all U.S. facilities receiving public funds for substance abuse treatment. Data collected come from admissions and discharges.

Admissions components involved individuals' demographic characteristics, primary, secondary substance use, secondary substance use, tertiary substance use, route of administration, frequency of use, age at first use, and source of referral to treatment (SAMHSA, 2019). Besides, it included a number of prior treatment episodes and service types. While discharges information included the type of service at discharge, length of stay, and reason for discharge (SAMHSA, 2019). Only three states were excluded in TEDS-D 2017, including Georgia, Oregon, and West Virginia, for lack of sufficient data reporting (SAMHSA, 2019).

Operationalization

The researcher used the 2017 TEDS-D codebook in the definition of the variables of interest.

Age: Using TEDS-D of 2017, the variable was used as the date of birth of the patient at admission (SAMHSA, 2019). The variable was measured as categorical and recorded into a different variable named Age_Group with four categories. The new recoded age variable comprises of five subcategories, including 1= "18-34", 2= "35-44", 3= "45-54", and 4= "55 and older". Individuals aged less than 18 were excluded.

Education: The education variable was described in the TEDS-D as the highest level of school years completed by subjects (SAMHSA, 2019). The variable has six subcategories but was recoded into four subcategories, including [1=Primary (<8 years), 2=Secondary (9-11years), 3=High School (12years), 4=College (13-15years), 5=Graduate (16 and more)] for easier analysis. The researcher used education as a categorical variable.

Employment status: This variable specifies the subject's employment status at the time of admission and has four subcategories (SAMHSA, 2019). It includes "Full-time, Part-time, Unemployed, Not in the labor force" (SAMHSA, 2019). The variable was measured as categorical in this study.

Race: Is "a multidimensional social construct and is considered as a predictor of exposure to external health risks posed by environmental, social, and behavioral factors" (Ford & Kelly, 2005). In the United States, race is defined as "White, Blacks or African American, Asian, American Indians and Alaska Native, Native Hawaiian and Other Pacific Islander, or other (U.S. Census Bureau, 2019). The researcher applied the defined variable in the 2017-TEDS-D. Race was recoded and considered in analysis as 1= Native Americans (Alaskans, American Indians, Pacific Islanders), 2=Blacks, 3=Whites, and 4=All others (other single and two or more races). The variable was measured as categorical. Latinos group was not listed in the TEDS-D survey.

Gender: Is defined as a social construct, representing biological and physiological differences between both sexes (female and male) (WHO, 2020). The variable of gender designates the subject's biological sex (Male and female), as described in the 2017-TEDS (SAMHSA, 2019). It was measured on the categorical level (1=Male and 2=Female).

Marital status: Refers to subject conjugal condition. This variable is termed in the TEDS-D ''Never married,'' 'Now married," "Separated," and "Divorced, widowed'' (SAMHSA, 2019). The same definition of "marital status" was applied in this study as categorical.

Health insurance coverage: Designates the subject of health insurance status at the time of admission (SAMHSA, 2019). The variable was measured as categorical and encompassed various labels, including “Private insurance, Blue Cross Shield, HMO,” “Medicaid,” “Medicare, other,” “None.” In this analysis, the variable was recoded into HLTHINS_Group by combining “Private insurance” and “Government insurance” into one category (1=Insured), and “None” (not having insurance coverage) was recoded into another category 0=Uninsured.

Reason for discharges or discontinuance of treatment: “Indicates the outcome of treatment or the reason for transfer or discontinuance of treatment” (SAMHSA, 2019). The variable was used as categorical and had several subcategories, including “Treatment completed,” “Dropped out of treatment,” “Terminated by the facility,” “Transferred to another treatment program or facility,” “Incarcerated,” “Death,” and “Other” (SAMHSA, 2019). In this analysis, the variable was recoded into Reason_Group to form two categories (1=Treatment completed and 0=Treatment not completed).

Opioid abuse: signifies other opiates/synthetics reported at admission by subjects as their primary substance use, including buprenorphine, codeine, hydrocodone, hydromorphone, meperidine, morphine, opium, oxycodone, pentazocine, propoxyphene, tramadol, and any drug having morphine-like effects (SAMHSA, 2019). This variable was measured as categorical. The variable stayed intact, as described in the codebook. It has two subcategories, including 1= “substance reported” at admissions) and 0= “substance not reported” at admissions for easier analysis.

Data Analysis Plan

The data collected analysis involved the use of the Statistical Package for the Social Sciences, version 25(SPSS). Indiana sub-data was extracted from the TEDS-D. All missing data were eliminated following the missing at random (MAR) procedures to ensure accuracy of the data. The independent or predictors variables considered in this analysis were sociodemographic factors (age, gender, race, education, employment status, and marital status) and health insurance status. The two independent variables were measured as categorical. Whereas the dependent or outcome variables were identified as binary. Opioid abuse (opiates/synthetics abuse) was defined as “Substance abuse not reported” vs. “Substance abuse reported." The outcome variable treatment completion was defined as “Treatment not completed” vs. “Treatment completed." This study's research questions were answered, and hypotheses tested using statistical analyses such as descriptive statistics, chi-square, and logistic regression.

Research Question 1: Is there any association between sociodemographic factors and treatment completion for opioid abusers among residents in Indiana?

$H_0$1: There is no association between sociodemographic factors and treatment completion for opioid abusers among residents in Indiana.

H_a1: There is an association between sociodemographic factors and treatment completion for opioid abusers among residents in Indiana.

RQ2: Is there any association between health insurance coverage and treatment completion for opioid abusers in Indiana?

$H_0$2: There is no association between health insurance coverage and treatment completion for opioid abusers in Indiana

*H*a2: There is an association between health insurance coverage and treatment completion for opioid abusers in Indiana

RQ3: Is there any association between health insurance coverage and treatment completion for opioid abusers in Indiana after controlling for sociodemographic factors?

$H_0$3: There is no association between health insurance coverage and treatment completion for opioid abusers in Indiana after controlling for demographic factors.

*H*a3: There is an association between health insurance coverage and treatment completion for opioid abusers in Indiana after controlling for sociodemographic factors.

It is essential to point out that descriptive statistics do not lead to conclusions regarding any hypotheses that might have been formulated (Laerd Statistics, 2018). Ultimately, descriptive statistics are just a way to describe the data analyzed. This makes descriptive statistics more critical when analyzing data because of their ability to allow a simpler interpretation of the data (Laerd Statistics, 2018). This can be done by presenting the results in tables or graphs. The statistical test Chi-square is generally known for testing correlations between categorical variables. In this analysis, the chi-square test's null hypothesis considers that no relationship exists on the population's independent categorical variables (Statistics Solutions, 2019). The Chi-square statistic is displayed as an option when requesting a crosstabulation in SPSS. Logistic regression analysis is the appropriate choice to analyze when the dependent variable is dichotomous (Statistics Solutions, 2020). Logistic regression is applied in describing data and clarifying the association between one dependent binary variable and one or more variables (Statistics Solutions, 2020). The expected results in this analysis will be presented in the form of odds ratio (OR), confidence interval (CI), and p-value.

For Research Question 1 (RQ1):

Descriptive statistics were conducted to display data summary for sociodemographic characteristics (age, race, gender, education, employment status, and marital status). Preliminary chi-square tests and multivariate logistic regression between sociodemographic attributes and opioid abuse (opiates/synthetics abuse) were performed to evaluate their association. Besides, basic chi-square tests and multivariate logistic regression were conducted to assess the relationship between sociodemographic factors and treatment completion outcomes.

For Research Question 2 (RQ2):

Descriptive statistics were carried out to display health insurance coverage and the outcome variable of treatment completion. The researcher used chi-square tests and bivariate logistic regression to evaluate the relationship between health insurance coverage and treatment completion.

For Research Question 3 (RQ3)

A multivariate logistic regression was run to assess the association between health insurance and treatment completion after adjusting for sociodemographic factors (age, race, gender, education, marital status, and employment status).

Threats to Validity

It has been demonstrated that the main threats to the reliability and validity of secondary data analysis evolve from the accuracy of the approaches used during the primary collection of such data (Boo & Froelicher, 2013). Issues may come from survey sampling, data collection, non-response, and missing data. The investigator did not participate in the initial research design and data collection; it is imperative to comprehend the accuracy of the dataset being investigated (Boo & Froelicher, 2013). In this study, there might be potential threats to reliability and validity. SAMHSA reported that an external factor, such as funding availability, could threaten the validity of this study (SAMHSA, 2019). Evidence suggested that states with higher funding tend to admit many substance-using individuals for treatment (SAMHSA, 2019).

On the other hand, funding constraints may lead states to limit their ability to admit a larger number of substance abusers; hence, it enabled them to target only special populations in their areas (SAMHSA, 2019). Another threat that might influence the results was that several states considered many admissions for the same patient, meaning data represent admissions only instead of the client (SAMHSA, 2019). Thus, data might contain several entries for one client. This might potentially affect the reliability and validity of the study. Also, non-response and missing information in the national survey might influence the validity of the overall results.

However, the extracted data from Indiana, which was examined in this study, seemed accurate. The data contained a large sample and an insignificant number of missing cases. TEDS is also one of the nation's most dependable data sources for substance abuse and mental health. Researchers are urged to access and utilize SAMHSA data repository files for public health purposes (SAMHSA, 2019). Therefore, TEDS data files are accurate and trustworthy. In analyzing the data, the researcher used statistical regression and randomization to overcome potential validity threats. Nonetheless, all missing data from the extracted Indiana sub-dataset were eliminated using the MAR process. Therefore, the statistical data analysis yielded accurate and precise results from the study.

Ethical Procedures

Researching human subjects can lead to ethical challenges. Public health ethics deal with recognizing, analyzing, and resolving ethical issues derived from public health practice and research (Coughlin, 2006). Ethical challenges in public health are usually linked to the necessity of public health professionals to obtain and use scientific knowledge to protect the public's general health while respecting the rights of individuals (Coughlin, 2006). Emphasizing ethical issues when conducting human subjects' research can facilitate effective planning, implementation, and improvement of public health plans and research (Coughlin, 2006).

The present secondary data analysis study examined data from 2017 Treatment Episode Data Set Discharges. The datasets were retrieved from Substance Abuse and Mental Health Data Archive (SAMHDA), and Indiana subdatasets will be extracted. The datasets were publicly available and can be accessed at: https://www.datafiles.samhsa.gov/ dy-dataset/teds-d-2017-ds0001-teds-d-2017-ds0001-nid18480. Data are de-identified and publicly accessible. When the data were initially collected, the researcher understood that a consent form was given to participants, and the results will be used for future research. Therefore, participants' confidentiality in this data analysis would not be affected.

Prior to analyzing the datasets in this study, the proposal was submitted to the Walden Institutional Review Boards for review. Approval would be granted to the investigator or researcher before the start of data analysis to ensure research compliance with the university's ethical standards as well as U.S. federal regulations. Information about opioid abuse subjects, including their demographics, substance use, health insurance, and treatment completion status, were accessible from the public domain through SAMHDA. In this secondary data, the information being treated would be protected under pass-worded computer. There was no conflict of interest involved in the process of this research, the dataset was publicly available.

Summary

Substance abuse is a growing socio-medical problem. The researcher applied a quantitative cross-sectional design by extracting Indiana from the 2017 TEDS-D datasets. The study analyzed the association between sociodemographic factors (age, gender, race, employment, education, marital status) and treatment completion status for opioid abuse in Indiana. Further, it assessed the association between health insurance coverage and treatment completion. A simple random sampling strategy to draw a representative sample was applied because of its ability to offer subjects an equal chance of being selected. Included in this data analysis were individuals aged 18 and older. G*Power software was used to determine the sample size of 988 participants from the target population of Indiana. The investigator performed various statistical tests, including descriptive statistics, chi-square, and multivariate logistic regression, using IBM SPSS version 25. This cross-sectional study's overall results will help promote positive social change in Indiana by designing and implementing policies to reduce the opioid abuse burdens. The next chapter (chapter 4) will discuss the introduction, data collection, and study outcomes.

Chapter 4: Results

Introduction

In this study, I examined the association between sociodemographic factors (i.e., age, gender, race, marital status, employment status, and education level) and successful treatment completion outcomes among opioid abusers in Indiana aged 18 years and older. The present study also sought to investigate the association between health insurance coverage and treatment completion outcomes for opioids abusers in Indiana among individuals aged 18 years and older. I formulated the following research questions along with subsequent hypotheses to conduct this study:

RQ1: Is there any association between sociodemographic factors and treatment completion for opioid abusers among residents in Indiana?

$H_0$1: There is no association between sociodemographic factors and treatment completion for opioid abusers among residents in Indiana.

H_a1: There is an association between sociodemographic factors and treatment completion for opioid abusers among residents in Indiana.

RQ2: Is there any association between health insurance coverage and treatment completion for opioid abusers in Indiana?

$H_0$2: There is no association between health insurance coverage and treatment completion for opioid abusers in Indiana.

H_a2: There is an association between health insurance coverage and treatment completion for opioid abusers in Indiana.

RQ3: Is there any association between health insurance coverage and treatment completion for opioid abusers in Indiana after controlling for sociodemographic factors?

$H_0$3: There is no association between health insurance coverage and treatment completion for opioid abusers in Indiana after controlling for sociodemographic factors.

H_a3: There is no association between health insurance coverage and treatment completion for opioid abusers in Indiana after controlling for sociodemographic factors.

In this analysis, the investigator adjusted sociodemographic factors to evaluate the association between health insurance coverage and treatment completion outcomes after adjusting the potential confounding effects of age, gender, race, employment, education, and marital status using multivariate logistic regression. Overall, chapter 4 will discuss data collection process used and the results of the data analysis of the study.

Data Collection

This research used TEDS-D archival data from SAMHSA, a national collection of annual discharges from substance use treatment services in 2017. TEDS-D represents admissions to licensed or certified facilities by state agencies for substance use treatment services; those facilities are mainly sponsored by states or drug agencies (SAMHSA, 2019). The TEDS-D is a nationally representative sample, although it does not include all substance use treatment facilities in the United States. The data were de-identified and were publicly available. Prior to analyzing the data, the researcher obtained the proposal's approval from Walden University Internal Review Board (IRB). The researcher IRB approval on November 17th, 2020, and the approval number was 11-17-20-0721940.

Within two days after the IRB approval, I accessed the SAMHSA website, and TEDS datasets were transferred on SPSS and stored in a password-protected USB key for analysis. The researcher then extracted Indiana state (#18 in the codebook) data from the national survey and analyzed the variables of interest. It included sociodemographic attributes (i.e., age, gender, race, employment status, education level, and marital status); health insurance coverage status; reported opioid abuse at admissions and completed treatment at discharge. We expected the baseline for education, marital status, employment status, gender, race, age, and health insurance coverage to be high school level, single, full-timers, female, whites, age group 18-34 years, and insured, respectively.

There was a total of 21,611cases generated for Indiana from the TEDS-D datasets, which represented 1.3% of the total cases in the national survey. After the Indiana datasets were analyzed and missing cases were removed, the number dropped to 20,822 cases. Following the inclusion and exclusion criteria, the analytic sample used in this study was set to be 20,822. Using SPSS, descriptive statistics, preliminary chi-square were applied. Additionally, bivariate and multivariate logistic regression analyses were the main statistical tests used and the results were reported in odds ratio. The dependent variables were treatment completion and opioid abusers. The independent variables were health insurance and sociodemographic factors of education, marital status, employment status, gender, race, and age. The outcomes and independent variables were defined and measured as follow:

Table 2

Variables and Coding

Variable	Coding
Age (IV)	1= “55 and older” 2= “45-54” 3= “35-44” 4= “18-34”.
Gender (IV)	1= “Male” 2= “Female”
Race (IV)	1= “Native Americans” 2= “Blacks or African Americans” 3= “All Others” 4= “Whites”
Education (IV)	1= “Primary” (<8 years) 2= “Secondary” (9-11years) 3= “College” (13-15years) 4= “Graduate” (16 and more) 5= “High School” (12years)
Marital status (IV)	1= “Divorced, widowed’’ 2= “Separated” 3= “Now married” 4= “Never married’’
Employment (IV)	1= “Not in the labor force” 2= “Unemployed” 3= “Part-time” 4= “Full-time”
Health insurance coverage (IV)	0= “Uninsured” 1= “Insured”
Opioid abuse (DV)	0= “substance not reported” 1= “substance reported”
Treatment completion (DV)	0= “Treatment not completed” 1= “Treatment completed”

Results

Research Question 1

Descriptive statistics for association sociodemographic factors and opioids abusers

I performed descriptive statistics for sociodemographic factors, opioid abuse (Other opiates/synthetics reported at admission), and treatment completion outcomes (reason to group). The respondents' sociodemographic characteristics included age, gender, race, education, employment status, and marital status. Data were summarized in table 3, including frequency distribution and a percentage per category of each variable. Males represented 59.9 % of the sample, while females made up 40.1 %. The sample was made up of 49.1 % of high school level, followed by secondary (24.0%), college (20.3%), primary (3.8%), and graduate (2.8%). Among respondents, 63.1 % represented "Never married", followed by "Divorced, widowed" (21.5%), "now married" (14.1 %), and "Separated" (1.4%). The sample was made up of 40.7% of unemployed, 31.6 % of full-time workers, 16.3% of individuals not in the labor force, and 11.3% of part-time workers. Regarding the age group frequency distribution, the sample comprised of 18-34 (52.1%), 35-44 (25.0%), 45-54 (17.2%), and 55 and older (5.7%). There were more whites recorded in the sample accounting for 80.8%, Blacks or African Americans (13.9%), All Others (0.4%), and Native Americans (4.9%). Among participants, 19.9 % reported abusing opioids, while 80.1% did not report abusing opioids. Finally, 29.7% of the sample completed treatment successfully.

Table 3

Descriptive statistics demographic characteristics of sample

Variable	Category	Frequency *(N)*	Percent (%)
Education (IV)	Primary	782	3.8 %
	Secondary	4990	24.0 %
	High School	10229	49.1%
	College	4235	20.3%
	Graduate	586	2.8%
Marital Status (IV)	Never Married	13134	63.1%
	Now married	2928	14.1%
	Separated	284	1.4%
	Divorced, Widowed	4476	21.5%
Employment Status (IV)	Full-time	6590	31.6%
	Part-time	2355	11.3%
	Unemployed	8479	40.7%
	Not in labor force	3398	16.3%
Biologic sex (IV)	Male	12474	59.9%
	Female	8348	40.1%
Race (IV)	Native Americans	80	0.4%
	African Americans	2897	13.9%
	Whites	16819	80.8%
	All others	1026	4.9%
Age (IV)	18-34	10856	52.1%
	35-44	5200	25.0%
	45-54	3584	17.2%
	55 and older	1182	5.7%
Treatment completion status (DV)	Treatment not completed	14631	70.3%
	Treatment completed	6191	29.7%

Note. *N*=20822

Chi-square results for association between sociodemographic factors and opioid abusers

Chi-square was conducted to assess whether sociodemographic factors were associated with opioids abusers. The results from Chi-square for the association between the selected sociodemographic factors (education, marital status, employment status, gender, race, and age) and opioids abusers were statistically significant for all of them yielding a p-value < 0.05, with the effect size varying from small to medium.

The results from the analysis exhibited statistical significance between education and opioids abusers with [Pearson $\chi^2(4, N = 20822) = 18.028$, p = 0.001, Cramer's V= 0.029] (see tables 4 and table 5). Findings between marital status and opioids abusers were statistically significant with [Pearson χ^2 (3, N = 20822) = 38.540, p = 0.001, Cramer's V= 0.043] (see table 6 and 7). Besides, the association for employment status revealed significance with [Pearson χ^2 (3, N = 20822) = 51.717, p = 0.001, Cramer's V= 0.050] (see table 8 and 9). Also, gender showed significance with [Pearson χ^2 (1, N=20822) =142.480, p=0.001, Cramer's V=0.083] (see table 10 and 11). Furthermore, the association with race yielded statistical significance too with [Pearson χ^2 (3, N = 20822) = 492.672, p = 0.001, Cramer's V= 0.154] (see table 12 and 13). Finally, it demonstrated the relationship between age and opioids abuse was significant with [Pearson χ^2 (3, N = 20822) = 318.205, p = 0.001, Cramer's V= 0.124] (see table 14 and 15).

Table 4

Chi-square results education vs. opioids abusers

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	18.028[a]	4	0.001
Likelihood Ratio	18.245	4	0.001
Linear-by-Linear Association	435	1	0.510
N of Valid Cases	20822		

Table 5

Effect size for association education and opioids abusers

		Value	Approximate Significance
Nominal by Nominal	Phi	0.029	0.001
	Cramer's V	0.029	0.001
N of Valid Cases		20822	

Table 6

Chi-square for association marital status vs. opioids abusers

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	38.540[a]	3	0.000
Likelihood Ratio	38.092	3	0.000
Linear-by-Linear Association	24.908	1	0.000
N of Valid Cases	20822		

Table 7

Effect size for association marital status and opioids abuser

		Value	Approximate Significance
Nominal by Nominal	Phi	0.043	0.000
	Cramer's V	0.043	0.000
N of Valid Cases		20822	

Table 8

Chi-square for association between employment status and opioids abusers

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	51.717[a]	3	0.000
Likelihood Ratio	51.846	3	0.000
Linear-by-Linear Association	31.059	1	0.000
N of Valid Cases	20822		

Table 9

Effect size for association marital status and opioids abusers

		Value	Approximate Significance
Nominal by Nominal	Phi	0.050	0.000
	Cramer's V	0.050	0.000
N of Valid Cases		20822	

Table 10

Chi-square for association between gender and opioids abusers

	Value	Df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	142.480[a]	1	0.000		
Continuity Correction [b]	142.058	1	0.000		
Likelihood Ratio	140.663	1	0.000		
Fisher's Exact Test				0.000	0.000
Linear-by-Linear Association	142.473	1	0.000		
N of Valid Cases	20822				

Table 11

Effect size for association between gender and opioids abusers

		Value	Approximate Significance
Nominal by Nominal	Phi	0.083	0.000
Cramer's V		0.083	0.000
N of Valid Cases		20822	

Table 12

Chi-square for association between race and opioids abusers

	Value	df	Asymptotic Significance
Pearson Chi-Square	492.672[a]	3	0.000
Likelihood Ratio	616.124	3	0.000
Linear-by-Linear Association	235.528	1	0.000
N of Valid Cases	20822		

Table 13

Effect size for association between race and opioids abusers

		Value	Approximate Significance
Nominal by Nominal	Phi	0.154	0.000
	Cramer's V	0.154	0.000
N of Valid Cases		20822	

Table 14

Chi-square for association between age and opioids abusers

	Value	df	Asymptotic Significance
Pearson Chi-Square	318.205[a]	3	0.000
Likelihood Ratio	350.593	3	0.000
Linear-by-Linear Association	301.720	1	0.000
N of Valid Cases	20822		

Table 15

Effect size for association age and opioids abusers

		Value	Approximate Significance
Nominal by Nominal	Phi	0.124	0.000
	Cramer's V	0.124	0.000
N of Valid Cases		20822	

Multivariate logistic regression for association between sociodemographic factors and *opioids abusers*

The researcher performed a multivariate logistic regression analysis to examine if age, gender, race, education, marital status, and employment status predicted opioid abuse (other opiates/synthetics). Recall that other opiates/synthetic comprised buprenorphine, codeine, hydrocodone, hydromorphone, meperidine, morphine, opium, oxycodone, pentazocine, propoxyphene, tramadol, and any other drug having morphine-like effects). In this analysis, the dependent variable of interest was opioid abuse (other opiates/ synthetics). The predictor variables included education, marital status, employment status, gender, race, and age. In this logistic regression model in table 16, the reference groups for education, marital status, employment status, gender, race, and age were high school, never married, full-time, female, whites, and age group 18-34, respectively.

Education level: In the multivariate logistic regression (table 16), high school educational level was used as the reference category. It was expected that having low educational is more likely to abuse drug (Gul & Sharma, 2017).The results demonstrated that only secondary and graduate levels were statistically significant. The results demonstrated that compared to high school level, secondary level was 1.2 times more likely[OR=1.189, 95% CI (1.088, 1.299), $p<0.0001$] to abuse opioid; graduate level was1.3 times more likely [OR = 1.269; 95% CI: .1.011, 1.592, p<0.05] to abuse opioids in Indiana compared to high school level. However, the differences across group levels showed no significance for primary education level (β = .121, S.E. = .096, Wald = 1.602, p = .206), approaching significance for college level (β = .088, S.E. = .047, Wald = 3.499, p = .061), and significance for secondary level (β = .173, S.E. = .045, Wald = 14.662, p = .000), and graduate level (β = .238, S.E. = .116, Wald = 4.236, p = .040).Therefore, secondary level and graduate level were associated with opioids abusers in Indiana compared to high school level.

Marital status: The model considered 'Never married' as a reference category. The results demonstrated statistical significance across all marital status categories. The results demonstrated that those with 'divorced, widowed' marital status compared to 'Never married' were less likely to abuse opioids in Indiana [OR=0.809, 95% CI (0.741, 0.884), $p<0.0001$]. The 'Separated' marital status was less likely than 'Never married' to abuse opioids [OR=0.621, 95% CI (0.460, 0.838), $p<0.05$]; 'Now married' marital status was less likely than 'Never married' to abuse opioids [OR= 0.778, 95% CI (0.704, 0.860), $p<0.0001$]. Therefore, 'Never married' marital status or single was more likely to abuse opioids compared to divorced/widowed, separated, and now married. Nonetheless, the model (table 16) showed differences across marital status to be significant for all group levels including divorced/widowed (β = -0.212, S.E. = .045, Wald = 21.851, p = .000), separated (β = -0.476, S.E. = 0.153, Wald = 9.687, p = .002), and now married (β

=-0.251, S.E. = 0.051, Wald = 23.990, p = .000). The results showed the odds ratio for marital status to be <1 and a β negative across all marital status levels, suggesting that there is a statistical difference between marital status and opioids abuse. Thus, the null hypothesis is rejected, and that there is an association between marital status and opioids abusers. Basically, single people were at highest risk compared to all other groups.

Employment status: In this group, full-time was used as the reference category. The model showed statistical significance for 'not in labor force' and unemployed but did not for part-timers. It showed that those in 'not in labor force' status was less likely than full-timers to abuse opioids [OR=0.736, 95% CI (0.658, 0.822), p<0.0001] (see table 16). Also, compared to full-timers, unemployed participants were less likely [OR= 0.749, 95% CI (0.688, 0.815), p<0.0001] to abuse opioids. Nevertheless, the outcomes indicated differences across the group levels to be significant for 'not in labor force' (β = -0.307, S.E. = .057, Wald = 29.067, p = .000), unemployed (β = -0.289, S.E. = .043, Wald = 44.969, p = .000), and non-significant for part-timers (β = -0.096, S.E. = 0.064, Wald = 2.211, p = .137). Thus, full-timers were more likely to abuse opioids in Indiana.

Gender: The model considered female as the reference category for gender. The results demonstrated significance for male sex (see table 16). The results showed that compared to female, male was 1.3 times more likely (OR=1.298, 95% CI (1.207, 1.395), p<0.0001) to abuse opioids. Also, the model showed a β positive (β=0.261, S.E. = .043, Wald = 44.969, p = .000). Based on these outcomes, the null hypothesis is rejected. Thus, there is an association between gender and opioids abusers and that female had a lower risk of reporting opioids abuse in Indiana.

Race: The reference category in this group is whites. The model suggested that there was a statistical significance across all race categories. The results suggested that compared to whites, Native Americans were 2.7 times more likely [OR=2.667, 95% CI (1.220,5.831), $p<0.05$] to abuse opioid; Blacks or African Americans were 4.6 times more likely [OR = 4.583; 95% CI (3.875, 5.421), p<0.0001]; All Others including Asians, other single race, two or more races were 1.6 times more likely [OR=1.637, 95% CI: 1.372, 1.953, p<0.0001] to abuse opioids in Indiana. It showed that whites had the lower risk of reporting opioids abuse in Indiana. Additionally, the differences across group levels showed statistical significance for all group levels including Native Americans ($\beta = .891$, S.E. = .399, Wald = 6.045, $p = .014$), Blacks or African Americans ($\beta = 1.522$, S.E. = .086, Wald = 315.768, $p = .000$), and All Others ($\beta = .493$, S.E. = .090, Wald = 29.838, $p = .000$). The model demonstrated the odds ratio for race levels to be greater than 1 and a β positive across all race categories. The null hypothesis is rejected; thus, there is association between race and opioids abusers in Indiana and that whites have lower risk of reporting opioids abuse.

Age: The reference category in this group is 18-34 years old. The outcomes showed statistical significance for all categories. It showed that compared to age group 18-34, individuals aged 35-44 were 1.2 times more likely [OR=1.212,95%CI (1.114, 1.319), $p<.0001$]; 45-54 were 2.2 times more likely [OR=2.226, 95%CI (1.987, 2.495), $p<.0001$]; age group 55 and older were 3.0 times more likely [OR=2.976, 95%CI (2.401, 3.690), $p<.0001$] to report opioids abuse in Indiana. The outcomes showed differences across group levels to be statistically significant for 35-44 ($\beta = .192$, S.E. = .043, Wald =

19.841, *p* = .000), 45-54 (β = .800, S.E. = .058, Wald = 189.558, *p* = .000), and 55 and older (β = 1.091, S.E. = .0110, Wald = 99.057, *p* = .000).The null hypothesis is rejected; therefore, there is an association between age and opioids abusers in Indiana. Younger people have lower risk of reporting opioids abuse.

Table 16

Multivariate results for association sociodemographic factors and opioids abusers

Variables	B	S. E	Wald	df	Odds ratio	95% confidence interval	Significance p
Education							
Primary	.121	.096	1.602	1	1.129	0.936-1.361	0.206
Secondary	.173	.045	14.662	1	1.189	1.088-1.299	0.000***
College	.088	.047	3.499	1	1.092	0.996-1.198	0.061
Graduate	.238	.116	4.236	1	1.269	1.011-1.592	0.040*
High school (reference)	----			--			
Marital status							
Divorced, widowed	-.212	.045	21.851	1	0.809	0.741-0.884	0.000***
Separated	-.476	.153	9.687	1	0.621	0.460-0.838	0.002**
Now married	-.251	.051	23.990	1	0.778	0.704-0.860	0.000***
Never married (ref.)	----			--			
Employment status							
Not in labor force	-.307	.057	29.067	1	0.736	0.658-0.822	0.000***
Unemployed	-.289	.043	44.969	1	0.749	0.688-0.815	0.000***
Part-time	-.096	.064	2.211	1	0.909	0.801-1.031	0.137
Full-time (ref.)	----			--			
Gender							
Male	.261	.037	49.925	1	1.298	1.207-1.395	0.000***
Female (ref.)	----			--			
Race							
Native Americans	.891	.399	6.045	1	2.667	1.220-5.831	0.014*
Blacks	1.522	.086	315.768	1	4.583	3.875-5.421	0.000***
All others	.493	.090	29.838	1	1.637	1.372-1.953	0.000***
Whites (ref.)	----			--			
Age							
35-44	.192	.043	19.841	1	1.212	1.114-1.319	0.000***
45-54	.800	.058	189.558	1	2.226	1.987-2.495	0.000***
55 and older	1.091	.110	99.057	1	2.976	2.401-3.690	0.000***
18-34 (ref.)	----			--			

Note: p=significance at 95% CI p >0.05, p<0.05*, p < 0.005**, p < 0.0001***

Chi-square and multivariate logistic regression results for association sociodemographic factors and treatment completion

Chi-square results for association sociodemographic and treatment completion Chi-square tests were performed examine whether an association exists between sociodemographic factors and opioids abusers. The results from Chi-square tests revealed that the association between sociodemographic factors and treatment completion was significant ($p<0.05$) for all of them except for race ($p>0.05$). Findings for education demonstrated significance with [Pearson χ^2 (4, N = 20822) = 45.690, p = 0.0001, Cramer's V= 0.047] (see tables 17 and table 18). Findings in tables 19 and 20 showed significance for marital status with [Pearson χ^2 (3, N = 20822) = 8.849, p = 0.031, Cramer's V= 0.021].

Also, employment status demonstrated the association to be statistically significant with [Pearson χ^2 (3, N = 20822) = 344.621, p = 0.0001, Cramer's V= 0.129] (see table 21 and table 22). The results from chi-square analysis revealed that sociodemographic characteristics of gender was significant with [Pearson χ^2 (1, N=20822) =39.094, p=0.0001, Cramer's V=0.043] (see table 23 and table 24). However, race did not yield significance [Pearson χ^2 (3, N = 20822) = 6.461, p = 0.091, Cramer's V= 0.018] (see table 25 and table 26). Finally, the chi-square analysis between age and treatment completion status yielded statistical significance with [Pearson χ^2 (3, N = 20822) = 64.777, p = 0.0001, Cramer's V= 0.056] (see table 27 and table 28). Thus, these findings showed that the sociodemographic factors were associated with treatment completion using preliminary chi-square except for race.

Table 17

Chi-square for association between education and treatment completion outcomes

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	45.690[a]	4	0.000
Likelihood Ratio	45.294	4	0.000
Linear-by-Linear Association	41.926	1	0.000
N of Valid Cases	20822		

Table 18

Effect size for association education and treatment completion outcomes

		Value	Approximate Significance
Nominal by Nominal	Phi	0.047	0.000
	Cramer's V	0.047	0.000
N of Valid Cases		20822	

Table 19

Chi-Square results for association marital status and treatment completion outcomes

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	8.849[a]	3	0.031
Likelihood Ratio	8.815	3	0.032
Linear-by-Linear Association	1.692	1	0.193
N of Valid Cases	20822		

Table 20

Effect size for association marital status and treatment completion outcomes

		Value	Approximate Significance
Nominal by Nominal	Phi	0.021	0.031
	Cramer's V	0.021	0.031
N of Valid Cases		20822	

Table 21

Chi-square results for association employment status and treatment completion outcomes

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	344.621[a]	3	0.000
Likelihood Ratio	339.458	3	0.000
Linear-by-Linear Association	320.722	1	0.000
N of Valid Cases	20822		

Table 22

Effect size for association employment status and treatment completion outcomes

		Value	Approximate Significance
Nominal by Nominal	Phi	0.129	0.000
	Cramer's V	0.129	0.000
N of Valid Cases		20822	

Table 23

Chi-square results for association gender and treatment completion outcomes

	Value	Df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	39.094[a]	1	0.000		
Continuity Correction [b]	38.901	1	0.000		
Likelihood Ratio	39.323	1	0.000		
Fisher's Exact Test				0.000	0.000
Linear-by-Linear Association	39.093	1	0.000		
N of Valid Cases	20822				

Table 24

Effect size for association gender and treatment completion outcomes

		Value	Approximate Significance
Nominal by Nominal	Phi	-0.043	0.000
	Cramer's V	0.043	0.000
N of Valid Cases		20822	

Table 25

Chi-square results for association race and treatment completion outcomes

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	6.461[a]	3	0.091
Likelihood Ratio	6.331	3	0.097
Linear-by-Linear Association	0.987	1	0.0321
N of Valid Cases	20822		

Table 26

Effect size for association race and treatment completion status

		Value	Approximate Significance
Nominal by Nominal	Phi	0.018	0.091
	Cramer's V	0.018	0.091
N of Valid Cases		20822	

Table 27

Chi-square results for association age and treatment completion outcomes

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	64.777[a]	3	0.000
Likelihood Ratio	62.230	3	0.000
Linear-by-Linear Association	47.389	1	0.000
N of Valid Cases	20822		

Table 28

Effect size for association age and treatment completion outcomes

		Value	Approximate Significance
Nominal by Nominal	Phi	0.056	0.000
	Cramer's V	0.056	0.000
N of Valid Cases		20822	

Multivariate logistic regression results for association between sociodemographic factors and treatment completion

The researcher applied a multivariate logistic regression analysis to examine the association between sociodemographic factors (education, marital status, employment status, gender, race, and age) and opioids abusers. The dependent or outcome variable considered in this analysis was treatment completion status. The predictor variables included education, marital status, employment status, gender, race, and age. The multivariate logistic regression model in table 29 considered the reference category for education, marital status, employment status, gender, race, and age as high school, never married, full-time, female, whites, and age group 18-34, respectively.

Education: The baseline in this category is high school level. The model suggested college and graduate level to be statistically significant. Whereas it did not showed significance for primary and secondary levels. It showed that compared to high school level, those with college level were 0.912 less likely [OR=0.912, 95% CI (1.219, 1.752), $p<0.05$]; individuals with graduate level were 0.731 less likely [OR=0.731, 95% CI (0.614, 0.871), $p<0.0001$] to complete treatment. However, the model did not show significance for primary and secondary levels. Additionally, differences across group levels showed non-significance for primary ($\beta = 0.151$, S.E. = .087, Wald = 3.061, $p = .080$), secondary ($\beta = .066$, S.E. = .039, Wald = 2.895, $p = .089$); significance for college ($\beta = -0.092$, S.E. = .040, Wald = 5.222, $p = .022$) and graduate ($\beta = -0.313$, S.E. = .089, Wald = 12.294, $p = .000$). The model demonstrated that the odds ratio for college and graduate had a significantly lower likelihood of treatment completion compared to high school. Further research is needed to confirm or repudiate these findings.

Marital status: In this group, the reference category is 'never married.' The outcomes suggested that only divorce/widowed marital status showed significance. It demonstrated that compared to 'never married' marital status, those with divorced/widowed status were 1.1more likely [OR=1.132, 95% CI (1.046, 1.225), $p<0.005$] to complete treatment. However, it did not show significance for separated [OR=0.978, 95% CI (0.754, 1.267), $p<0.865$] and for 'now married' [OR=0.997, 95% CI (0.912, 1.089), $p<0.943$]. There is no association between marital status and treatment completion.

Employment status: Full-time is considered the reference category in the model. The results showed all categories to be statistically significant. It showed that compared to full-timers, individuals in 'not in labor force' were 2.0 times more likely [OR=2.042, 95% CI (1.853, 2.252), $p<0.0001$], unemployed were 1.8 times more likely [OR=1.785, 95% CI (1.662, 1.916), $p<0.0001$], and part-timers were 1.4 times more likely [OR=1.406, 95% CI (1.269, 1.557), $p<0.0001$] to complete treatment. It meant that full-timers have lower treatment completion rate than 'not in labor force', unemployed, and part-timers. Further, the differences across levels showed significance for 'not in labor force' (β = 0.714, S.E. = .050, Wald = 205.935, p = .000), unemployed (β = .579, S.E. = .036, Wald = 255.460, p = .000); part-timers (β = 0.341, S.E. = .052, Wald = 42.622, p = .000). It showed the odds ratio across all categories to be >1 and a β positive. The null hypothesis is rejected; thus, there is an association between employment status and treatment completion.

Gender: The reference category in gender group is female. The model showed significance for male (table 29). It demonstrated that compared to females, males were 0.923 times less likely [OR=0.923, 95% CI (0.866, 0.983), $p<0.05$] and [$\beta = -.081$, S.E. = .033, Wald = 6.108, $p = .013$] (see table 29). Thus, females had higher treatment completion rate than males.

Race: The reference category chosen in this group is whites. The overall logistic regression model showed that 'All others' were statistically significant (see table 29). It showed that compared to whites, 'All Others' were 0.9 times less likely to complete treatment with [OR=0.852, 95% CI (0.743, 0.976), $p< 0.05$] and [$\beta = -.161$, S.E. = .069, Wald = 5.348, $p = .021$]. However, the results did not show significance for 'Native Americans' [OR=0.822, 95% CI (0.515-1.312), $p> 0.05$] and for 'Blacks or African Americans' [OR=1.049, 95% CI (0.960, 1.147), $p>0.05$]. Whites were more likely to have higher treatment completion rate.

Age: The reference category for age is age group 18 to 34. The overall model showed significance across all categories. It suggested that compared to age group 18-34, individuals aged 35-44 were 0.517 times less likely [OR=0.517, 95% CI (0.452-0.591), $p<0.0001$] with OR<1. Also, it showed that age group 45 to 54 were 0.833 times less likely [OR=0.833, 95% CI (0.765-0.907), $p<0.0001$]; age group 55 and older were 0.918 times less likely [OR=0.918, 95% CI (0.851-0.990), $p<0.05$] to complete treatment compared to 18 to 34. Likewise, the differences across the age group levels were significant for age group 35-44 (β = -0.086, S.E. = .039, Wald = 92.851, p = .000); age group 45-54 (β = -0.183, S.E. = .043, Wald = 17.786, p = .000); and age group 55 and older (β = -0.659, S.E. = .068, Wald = 4.919, p = .027). Therefore, the null hypothesis is rejected, and I conclude that there is a negative association between age and treatment completion. This suggested that younger people have higher treatment completion rate than older people. That means, when you get older, it is less likely to complete treatment.

Table 29

Multivariate results for association between sociodemographic factors and treatment completion outcomes

Variables	B	S. E	Wald	df	Odds ratio	95% CI	Significance $p<0.05$
Education							
Primary	.151	.087	3.061	1	1.163	0.982-1.378	0.080
Secondary	.066	.039	2.895	1	1.069	0.990-1.154	0.089
College	-.092	.040	5.222	1	0.912	0.843-0.987	0.022*
Graduate	-.313	.089	12.294	1	0.731	0.614-0.871	0.000***
High school (reference)	----			--			
Marital status							
Divorced, widowed	.124	.040	9.432	1	1.132	1.046-1.225	0.002**
..Separated	-.022	.132	0.029	1	0.978	0.754-1.267	0.865
..Now married	-.003	.045	0.005	1	0.997	0.912-1.089	0.943
..Never married (ref.)	----			--			
Employment status							
..Not in labor force	.714	.050	205.935	1	2.042	1.853-2.252	0.000***
..Unemployed	.579	.036	255.460	1	1.785	1.662-1.916	0.000***
..Part-time	.341	.052	42.622	1	1.406	1.269-1.557	0.000***
..Full-time (ref.)	----			--			
Gender							
Male	-.081	.033	6.108	1	0.923	0.866-0.983	0.013*
Female (ref.)	----			--			
Race							
Native Americans	-.196	.239	.676	1	0.822	0.515-1.312	0.411
Blacks	.048	.046	1.113	1	1.049	0.960-1.147	0.292
..All Others	-.161	.069	5.348	1	0.852	0.743-0.976	0.021*
..Whites (ref.)	----			--			
Age							
..35-44	-.086	.039.0	92.851	1	0.517	0.452-0.591	0.000***
45-54	-.183	43	17.786	1	0.833	0.765-0.907	0.000***
..55 and older	-.659	.068	4.919	1	0.918	0.851-0.990	0.027*
..18-34 (ref.)	----			--			

Note: p=significance at 95% CI p >0.05, p<0.05*, p < 0.005**, p < 0.0001***

Research Question 2

Descriptive statistics for association health insurance vs. treatment completion

Descriptive statistics presented in table 28 for both variables (health insurance coverage and treatment completion) revealed *N*= 20822 valid cases processed and zero missing cases. The sample comprised of *N*=6926 individuals aged 18 and older who were uninsured, accounting for 33.3%. While *N*= 13896 participants who were insured with any insurance coverage, including private or government, representing 66.7% of the total sample (Table 28). Among participants, there were a total of *N*=14631 who did not complete their treatment accounting for 70.3%. There were dropped out of treatment, terminated by the center, transferred to a new facility or program, incarcerated, or dead. Those who did complete treatment successfully represented 29.7%.

Table 30

Descriptive statistics of health insurance coverage and treatment completion outcomes

Variables	Category	Frequency (*N*)	Percent (*%*)
Health Insurance coverage	Uninsured	6926	33.3
	Insured	13896	66.7
Treatment Completion stat	Treatment not completed	14631	70.3
	Treatment completed	6191	29.7

Note: N=20822

Chi-square of association between health insurance coverage and treatment completion

Table 31 showed that among individuals who did not complete treatment for opioid abuse, the expected count for "uninsured" was 4866.7, while the observed count was 4521. For those insured, the expected count was 9764.3, while the observed count was 10110. Among individuals who completed the treatment for opioid abuse (treatment completed), the expected count for "Uninsured" was 2059.3, and the observed count for that same group was 2405. For the "Insured" group who did complete their treatment, the expected count was estimated at 4131.7, and the observed count was 3786.

The chi-square test results were shown in table 32. The findings demonstrated the association between health insurance coverage and successful treatment completion was statistically significant with [Pearson χ^2 (1, N = 20822) = 123.750, p = 0.0001, Cramer’s V= 0.77)] (see table 32 and table 33). This outcome in table 32, with a p-value less than 0.05, indicated strong evidence against the null hypothesis. Therefore, the null hypothesis was rejected, and the alternative hypothesis was accepted. This meant that there is an association between health insurance coverage and treatment completion and that having health insurance coverage predicted successful treatment completion. To understand the extent of the association between health insurance coverage and treatment completion, Cramer's V was run, and the result was presented in table 33. Cramer's V described the association's effect size, and the table showed the value to be 0.77. Therefore, the effect size of the association between health insurance coverage and treatment completion was large enough for the generalization of the findings.

Table 31

Crosstab between health insurance coverage and treatment completion outcomes

			Health insurance status		
			Uninsured	**Insured**	**Total**
Treatment Completion status	**Treatment not completed**	Count	4521	10110	14631
		Expected Count	4866.	79764.3	14631.0
	Treatment completed	Count	2405	3786	6191
		Expected Count	2059.3	4131.7	6191.0
Total		Count	6926	13896	20822
		Expected Count	6960.0	13896.0	20822.0

Table 32

Chi-square results for association between health insurance coverage and treatment completion outcomes

	Value	Df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	123.750[a]	1	.000		
Continuity Correction [b]	123.392	1	.000		
Likelihood Ratio	122.054	1	.000		
Fisher's Exact Test				.000	.000
Linear-by-Linear Association	123.744	1			
N of Valid Cases	20822				

Table 33

Effect size for association health insurance coverage and treatment completion outcomes

		Value	P
Nominal by Nominal	Phi	.077	.000
	Cramer's V	.077	.000
N of Valid Cases		20822	

Bivariate logistic regression

The inquirer ran a bivariate logistic regression to evaluate the association between health insurance coverage and treatment completion (see table 34). It is expected that having health insurance coverage (being insured) can have higher chance of treatment completion (Feder et al., 2019).The reference category in this analysis was 'Insured.' The outcomes of the analysis demonstrated statistical significance. It showed that compared to insured, uninsured individuals were less likely [OR=0.704, 95% CI (0.662, 0.749), $p<0.0001$] to complete treatment. The results also showed that (β =- 0.351, S.E. = .032, Wald = 123.219, p = .000) [table 34]. That meant that compared to 'Insured,' people who were uninsured (lacking insurance coverage) were 0.704 times (30%) less likely to complete opioids treatment. The model demonstrated that the null hypothesis is rejected and that having health insurance (being insured) is associated with treatment completion. Thus, 'Uninsured' individuals have a lower chance of completing the treatment.

Table 34

Bivariate results for association between health insurance coverage and treatment completion outcomes

Variable	B	S. E	Wald	df	Odds ratio	95% CI	*P*
Uninsured	-0.351	0.032	123.219	1	0.704	0.662-0.749	0.000
Insured (Ref)	-------			-------			

Research Question 3

Multivariate logistic regression between health insurance and treatment completion outcomes after adjusting for sociodemographic factors

The investigator conducted a multivariate logistic regression to examine the association between health insurance coverage and treatment completion after adjusting for age, gender, race, marital status, employment status, and education (Table 35). The outcome variable considered in this analysis was successful treatment completion. The predictor variable in this multivariate logistic regression was health insurance with sociodemographic factors adjusted. The investigator added education, marital status, employment status, gender, race, and age to the model. The results suggested that education was not associated with treatment completion. It did, however, showed significance with college and graduate. It demonstrated that compared to high school level, college were less likely [OR=0.915, 95% CI (0.846, 0.990), $p<0.05$], and graduate less likely [OR=0.739, 95% CI (0.620, 0.881), $p<0.05$] since OR is less than 1.00.

Besides, the outcomes revealed that marital status did not show significance. But it showed that compared to single, divorced/widowed were 1.140 times more likely [OR=1.140, 95% CI (1.053, 1.234), $p<0.05$] to complete treatment. Nonetheless, the results demonstrated significance for employment status. It did show that compared to full-timers, not in the labor force were 1.9 times more likely [OR=1.929, 95% CI (1.748, 2.128), $p<0.0001$]; unemployed were 1.8 times more likely [OR=1.801, 95% CI (1.677, 1.934), $p<0.0001$], and part-timers were 1.4 times more likely [OR=1.392, 95% CI (1.256, 1.542), $p<0.0001$] to complete treatment. Findings revealed that gender was not significant. Similarly, the results showed that race was not significant ($p>0.05$). It did nonetheless showed significance for age across all levels. That meant, compared to age group 18-34, age group 35 to 44 had lower likelihood [OR=0.509, 95% CI (0.445, 0.582), $p<0.0001$; age group 45 to 54 had lower likelihood [OR=0.826, 95% CI (0.759, 0.899), $p<0.0001$; and age group 55 and older had lower likelihood [OR=0.911, 95% CI (0.845, 0.983), $p<0.0001$] to complete treatment since OR is less than 1.00. Most importantly, the model showed that compared to insured, uninsured 0.722 times less likely [OR=0.722, 95% CI (0.678, 0.770), $p<0.0001$] to complete treatment. It also showed that after sociodemographic factors were adjusted, the OR increased from [OR=704, 95% CI (0.662-0.749), $p<0.0001$] to [OR=0.722, 95% CI (0.678, 0.770), $p<0.0001$]. I concluded an association exists between health insurance coverage and treatment completion and that employment status and age were confounders. Though, health insurance coverage is an independent factor that improves the chance of treatment completion.

Table 35

Multivariate results for association health insurance coverage and treatment completion outcomes after adjusting for sociodemographic factors

Variables	B	S. E	Wald	df	Odds ratio	95% confidence interval	Significance *p*<0.05
Health insurance status	-.325	.033	99.701	1	0.722	0.678-0.770	0.000***
..Uninsured	------			--			
Insured (Reference)				-			
Education							
Primary	.150	.087	3.007	1	1.162	0.981-1.378	0.083
Secondary	.068	.039	2.990	1	1.070	0.991-1.155	0.084
..College	-.089	.040	4.835	1	0.915	0.846-0.990	0.028*
..Graduate	-.302	.090	11.371	1	0.739	0.620-0.881	0.001***
..High school (ref.)	----			--			
Marital status							
..Divorced, widowed	.131	.040	10.502	1	1.140	1.053-1.234	0.001**
..Separated	-.019	.133	0.020	1	0.982	0.757-1.273	0.888
..Now married	-.008	.045	0.030	1	0.992	0.908-1.084	0.863
..Never married (ref.)	----			--			
Employment status							
..Not in labor force	.657	.050	171.441	1	1.929	1.748-2.128	0.000***
..Unemployed	.588	.036	261.582	1	1.801	1.677-1.934	0.000***
..Part-time	.331	.052	39.910	1	1.392	1.256-1.542	0.000***
..Full-time (ref.)	----			--			
Gender							
Male	-.049	.033	2.237	1	0.952	0.893-1.015	0.135
Female (ref.)	----			--			
Race							
Native Americans	-.213	.239	.795	1	0.808	0.506-1.291	0.373
Blacks	.061	.046	1.778	1	1.063	0.972-1.162	0.182
..All Others	-.148	.070	4.472	1	0.863	0.753-0.989	0.034*
..Whites (ref.)	----			--			
Age							
..35-44	-.676	.069.	96.930	1	0.509	0.445-0.582	0.000***
45-54	-.191	043	19.408	1	0.826	0.759-0.899	0.000***
55 and older	-.093	.039	5.789	1	0.911	0.845-0.983	0.016*
..18-34 (ref.)	----			--			

Note: p=significance at 95% CI p >0.05, p<0.05*, p < 0.005**, p < 0.0001***

Summary

This study design examined the association between sociodemographic factors (i.e., age, gender, race, education, marital status, and employment status) and treatment completion for opioids abusers in Indiana. The researcher applied descriptive statistics such as frequency distribution to display data summary. The study further assessed the association between health insurance coverage and treatment completion for opioid abusers in Indiana after controlling for sociodemographic factors using chi-square and logistic regression. A sample (N=20822) was used, accounting for 59.9% males and 40.1% females aged 18 and older. Almost half of the sample had a high school level (49%), and slightly over 20% had a college degree or higher. Individuals who were never married represented the sample's bulk (63%), and 22% were divorced/widowed. Descriptive statistics showed that 41% of the sample were unemployed, while 32% had a full-time job, and 11% had part-time employment. Most of the sample were Whites (81%) and Blacks or African Americans (14%). Also, participants in the study were aged 18-34 years old (52%), 35-44 (25%), and 45-54 (17%).

Basic chi-square tests performed exhibited a statistically significant association between sociodemographic factors and opioids abusers across all levels. The researcher conducted a multivariate logistic regression analysis to assess the association between sociodemographic characteristics and opioids abusers. The results demonstrated statistical significance ($p<0.05$) for divorced or widowed/ separated/now married compared to never married; male compared to female; Native Americans/ Blacks or African Americans/ All Others compared to whites; older age group compared to younger. Similarly, the outcomes revealed that never married were more likely to report opioids abuse, and that being females, whites, and younger showed lower risk of reporting opioids abuse in Indiana. Additionally, a multivariate logistic test for the association between sociodemographic factors and treatment completion showed significance ($p<0.05$) for not in labor force/unemployed/ part-timers compared to full-timers; male compared to female; older age groups compared to younger age group (18-34).The overall model revealed that being full-timers and younger is linked with lower treatment completion rate. However, it demonstrated that being females is associated with higher treatment completion rate. A bivariate model used to assess the association between health insurance coverage and treatment completion status showed significance and that being insured contributed to treatment completion outcome. After sociodemographic attributes of education, marital status, employment status, gender, race, and age were added to the model, health insurance coverage still showed significance. It showed that employment status, and age might be confounders on the association. The next section discussed interpretation of the results, limitations of the study, recommendations, implications for positive social change, and conclusion.

Chapter 5: Discussion, Conclusions, and Recommendations

Introduction

Substance abuse has been a longstanding health issue across the United Stated (Gomes et al., 2018). In Indiana, in 2017, opioid abuse had claimed 1,700 lives due to overdose Richard Fairbanks Foundation, 2018). Statistics showed individuals aged 18 and older were highly affected by substance abuse (NIDA, 2018). This study sought to investigate the association between sociodemographic factors (i.e., age, gender, race, marital status, employment status, and education level) and successful treatment completion outcomes among opioid abusers in Indiana aged 18 and older using 2017 Treatment Episode Data Set Discharges (TEDS-D) that can be accessed through the CDC WONDER. The current study also investigated the association between health insurance coverage and treatment completion outcomes for opioids abusers in Indiana among individuals aged 18 years and older. The study was conducted to advocate the expansion of health insurance coverage for substance abuse patients (including opioids) and improve treatment completion outcomes and access to care while reducing morbidity and mortality due to opioid abuse among Indiana residents.

A sample size of N=20922 was used in this analysis. Descriptive statistics showed that the sample was made up of 60% males and 40% females aged 18 and older. Data summary demonstrated individuals with high school levels accounted for 49%, secondary (24%), and those with college degrees accounted for slightly more than 24%. In this sample, 63% were never married, 22% were divorced/widowed, and 14% were married. Further, descriptive statistics revealed that 43% of the sample had a full-time or part-time job, while 41% were unemployed, 16% were not in labor force. The sample was made up of Whites (81 %,) Blacks or African Americans (14 %,) Native Americans (slightly over 1 %,) and the rest represented "All others." Moreover, the sample showed that 30% did report substance abuse. Additionally, there were 30% of individuals who did complete treatment in the sample. Pearson chi-square between sociodemographic factors and opioids abusers showed significance across all levels with a p-value less than 5%. Nevertheless, basic Chi-square tests between the same sociodemographic attributes and treatment completion showed statistical significance at all levels except for race.

Meaningful findings suggested a statistical significance correlation (p-value less than 5%) between marital status, gender, race, age, and opioids abusers. The results revealed that never married or single were more likely to report opioids abuse while females, whites, and younger people had a lower risk of reporting opioids abuse in Indiana. Similarly, the outcomes showed the association between employment status, gender, age, and treatment completion to be statistically significant. It demonstrated that females had a higher treatment completion rate, whereas full-timers and younger people had a lower treatment completion rate. Furthermore, the association between health insurance coverage and treatment completion was significant, and that uninsured individual had a lower chance of completing treatment. It suggested that marital status, employment status, and age were confounders in the association. The next sections will discuss the interpretation of my findings, the study's limitations, recommendations, implications for positive social change, and conclusion.

Interpretation of the Findings

This research fills the gaps by assessing the association between the selected sociodemographic factors and treatment completion status for opioids abusers. Also, it sought to evaluate the correlation between health insurance coverage and treatment completion status after sociodemographic factors were adjusted.

Research Question 1: Sociodemographic factors and treatment completion for opioids abuse

The findings were statistically significant for secondary and graduate levels. The outcomes approached significance for college level. That meant, compared to high school, secondary level was 1.2 times more likely [OR=1.189, 95% CI (1.088, 1.299), *p*<0.0001]; graduate-level was 1.3 times more likely [OR = 1.269; 95% CI: .1.011, 1.592, p<0.05] to abuse opioids. It demonstrated that when people are more educated, they are more likely to engage in substance abuse. These findings were different from studies by Gomes et al. (2018); Gul & Sharna., 2017; and Swendsen et al., 2009), which showed that education was strongly associated with substance abuse.

Concerning marital status, findings revealed that those with 'divorced, widowed' marital status were less likely to abuse opioids compared to 'never married.' Similarly, 'Separated' marital status was less likely than 'Never married' to abuse opioids; 'Now married' marital status was less likely than 'Never married' to abuse opioids. Therefore, 'Never married' marital status was more likely to abuse opioids than divorced/widowed, separated, and now married. The results showed the odds ratio for marital status suggested an association between marital status and opioids abusers. This study's results were consistent findings from Lamptey (2005); and Tavares et al.(2004). Other studies found single or never married to be a predictor of opioid abuse (Ray et al., 2017; and Swendsen et al., 2009). It could be that long-term opioid abusers are less likely to find spouses; thus, they are more likely to stay single, and some never get to marry. However, further research is needed to confirm these findings.

The results demonstrated that employment status was statistically significant across ‘not in labor force’ and unemployed, but non-significant for part-timers. It was assumed that the more people hold full-time employment, the less likely they engage in substance abuse activities. But the outcomes revealed that compared to full-timers, individuals in ‘not in labor force’ were less likely to report opioids abuse. Similarly, the results suggested that unemployed people were less likely than full-timers to abuse opioids. The outcomes represented a reversal that found full-time employment to have protective effects against drug problems (Simoni-Wastila& Strickler, 2011). However, in a previous study by Simoni-Wastila& Strickler (2011), the investigators did not find full-time and part-time employment status to be associated with opioids abuse. Besides, Henkel (2011) and Tavares et al. (2004) demonstrated unemployment to be a significant risk factor for substance abuse and dependence. Henkel (2011) further elaborated that unemployment can augment the risk of relapse after drug addiction treatment. More investigation is needed to understand the variations for sociodemographic employment status.

The current study results found that males have a higher risk of reporting opioids abuse than females, with a ratio of 1.3. Previous studies also had reported that being male had a greater likelihood than female to abuse opioids (Gomes et al., 2018; Lamptey, 2005; Ray et al.,2017; and Wisniewski et al. (2008). However, McCabe et al. (2017)) findings were contradictory and found that females had a higher risk of abusing opioids than male individuals. Another survey did not find any difference with gender (Swendsen et al., 2009). More study is needed to validate the current results.

Moreover, the results showed significance for all racial levels (p<0.05). Compared to whites, Native Americans were 2.7 times more likely to abuse opioids; It demonstrated that Blacks or African compared to whites were 4.6 times more likely to report opioids abuse. Compared to ‘All Others’ including Asians, other single race, two or more races were 1.6 times more likely to abuse opioids in Indiana. It showed that whites have a lower risk of reporting opioids abuse in Indiana. Other studies found that white people were more likely to abuse opioids (Lamptey, 2005; Ray et al., 2011; Simoni-Wastila& Strickler). However, other studies did not find any difference.

Furthermore, sociodemographic characteristic of age was significantly correlated with opioid abuse in this study. The outcomes revealed that compared to the age group 18-34, individuals aged 35-44 were 1.2 times more likely to report opioids abuse. Age groups 45-54 were 2.2 times more likely to report opioids abuse than individuals aged 18-34. Also, people aged 55 and older were 3.0 times more likely to report opioids abuse compared to the age group 18-34. These findings were consistent with the results from the surveys conducted by Ray et al. (2011) and Simoni-Wastila& Strickler (2011). On the other hand, some surveys revealed that drug abuse was more prevalent in adolescents (Gomes et al., 2018; Kolodny et al., 2015; McHugh et al.,2014; Ranjan et al., 2010 and

Wisniewski et al., 2008) and in younger people (Lamptey, 2005; Swendsen et al., 2009 and Tavares et al., 2004). Nonetheless, more investigation is needed to confirm these findings.

The association between the selected sociodemographic factors and treatment completion status had been assessed (see table 29). Findings revealed that college and graduate-level were statistically significant. However, the results showed non-significance for primary and secondary levels. It meant that compared to the high school level, individuals with college-level were 0.912 more likely to complete treatment. Similarly, individuals with graduate-level were 0.731 more likely to complete treatment. However, the model did not show significance for primary and secondary levels. This study's results aligned with previous findings from Newton-Howes & Stanley (2015). Also, surveys suggested that failure to complete treatment was positively associated with lower educational attainment (Brown, 2010; Knight et al., 2009). There is a need for more investigation to validate the results of this study.

Regarding marital status, the outcomes suggested that only individuals with divorce/widowed marital status were significant. It demonstrated that compared to 'never married' marital status, individuals having divorced/widowed status were 1.1 more likely to complete treatment. Separated and now married were more likely to complete treatment than never married or single, but these differences were not significant. Previous studies found different outcomes and that Whites were more likely to complete treatment (76.7%). More research is needed to confirm these results.

Besides, the results of this study yielded a statistical significance for employment status across all levels. It showed that compared to full-timers, individuals in 'not in labor force' were 2.0 times more likely to complete treatment; Unemployed were 1.8 times more likely, and part-timers were 1.4 times more to complete treatment when compared to full-timers. This could be related to lack of social support. Some studies found no difference between employment status and treatment completion (Bazargan-Hejazi et al., 2016 and Suntai et al., 2020), and another found unemployed to be predictive of treatment completion (Brown, 2010). Further research is needed.

Moreover, the results demonstrated that males were 0.923 times less likely to complete treatment than their counterparts' females. This meant that females have a higher treatment completion rate than males. The results were consistent with previous research conducted by Guerrero et al. (2014). On the contrary, other studies found that males had higher treatment completion rates than females (Bazargan-Hejazi et al., 2016; and Suntai et al., 2020). It is common to believe that women were more likely to receive services that match their needs than men. Nonetheless, Brown's (2020) survey did not find any difference between gender and treatment completion.

The outcomes of the study showed race not to be statistically significant. It does, however, showed significance for the ‘All Others’ race group. It meant that compared to whites, ‘All Others’ (Asians, other single race, and two or more races) were 0.918 times less likely to complete treatment. Other findings from Suntai et al. (2020) revealed that Blacks were less likely than whites to complete treatment. However, the study conducted by Brown (2010) found non-white ethnicity to be strongly correlated with treatment completion outcomes compared to whites.

Finally, the results of the study demonstrated age to be statistically significant at all levels. It showed that compared to age group 18-34, individuals aged 35-44 were 0.517 times less likely to complete treatment. Also, age groups 45 to 54 were 0.833 times less likely than age group 18-34 to complete treatment. Compared to age group 18-34, individuals aged 55 and older were 0.918 times less likely to complete treatment. The overall results demonstrated that younger people have a higher treatment completion rate than older people since the OR for all level was less 1.00. Further research could help figure out the reasons for this shift. Evidence suggested that older people would have better treatment outcomes than younger. Because as reported in a survey, older people do not face system-level barriers for treatment since they generally possessed public insurance coverage through Medicare, Tricare, and VA (Choi et al., 2014). The outcomes in this study showed that younger had higher treatment completion rates compared to older people. Previous research recognized some barriers that led to similar findings. It had been shown that substance abuse treatment barriers for older people included lack of readiness to discontinue use and lack of knowledge about services, treatment, and programs (Choi et al., 2014). Conversely, Choi et al. (2014) noted that younger people faced substance abuse treatment barriers such as cost, stigma, and confidentiality concerns. The study outcomes could be due to education. Tackling the epidemic of opioids has been one of the main focuses of public health policymakers in Indiana;

Education is the primary focus to help individuals understand the health consequences of opioid abuse (Indiana State Department of Health, 2018).

On the other hand, this study outcome were different from Suntai et al. (2020,) whose findings suggested that older people have higher treatment completion rates for substance abuse. Although older adults had higher odds of substance abuse treatment completion, the multivariate logistic regression model suggested differences among racial groups (Suntai et al., 2020). The study noted that Black older adults had a lower likelihood of completing substance use treatment than their White counterparts [OR= 0.630]. It showed that the difference had deepened between whites and Blacks subjects, with Blacks older adults being 34% less likely to complete treatment than Whites (Suntai et al., 2020).

Research Question 2: Association of Health insurance and treatment completion The study outcomes showed significance for health insurance coverage. It demonstrated that compared to insured, uninsured individuals were 0.704 times less likely to complete treatment. These study findings showed that 'Uninsured' individuals have a lower chance of completing the treatment than insured individuals. Previous studies found an association between health insurance coverage and successful treatment completion (Allcock et al., 2019; Mojtabai et al., 2020 and Olfson et al., 2018;). Research conducted by Mojtabai et al. (2020) reported that numerous privately insured adults with drug use disorders in the United States were not covered for drug use treatment. However, the article suggested that the Affordable Care Act's enaction introduced new benefits to cover individuals with substance use problems (Mojtabai et al., 2020). When assessed the correlation between having drug use treatment coverage and receiving treatment, Mojtabai et al. (2020) found that coverage was statistically significantly correlated with receiving treatment [OR= 2.09, 95% CI = 1.61–2.72, $p < .001$]. Additionally, the investigators examined such association in two simulated situations with participants who ignored their coverage (in one scenario, none of the participants had coverage and, the second scenario assumed that all participants had coverage.) The outcomes revealed that the association of drug treatment coverage with actual receipt of treatment was statistically significant in both scenarios yielding [OR = 2.46, 95% CI = 1.91–3.16, $p < .001$] and [OR = 1.46, 95% CI = 1.14–1.88, $p = .004$], respectively (Mojtabai et al., 2020). Olfson et al. (2019) found a significant increase in private insurance use among individuals aged 19-25 (8%) and 26-35 years old (1.2%) between 2008-2010 and 2011-2013. But the increase within the two groups did not differ between 2011-2013 to 2014-2016 with 3.2% and 3.8%, respectively. Also, a research conducted by Allcock et al. (2020) found that health insurance was strongly associated with both outpatient and inpatient care [OR: 1.28; 95% CI: 1.08–1.52; $p = 0.005$] and [OR: 1.52; 95% CI: 1.26–1.82; $p < 0.001$]. However, the studies' results noted the utilization of health insurance coverage to be low (Allcock et al., 2019; Motjabai et al., 2020 and Olfson et al., 2018).

Also, the more health insurance coverage people have the better chance of completing treatment for substance abuse. Having health insurance coverage is a strong predictor of drug treatment completion. Cummings et al. (2014) assessed the association between private insurance coverage for substance use disorders and specialty treatment among U.S. Adults. The analysis outcomes indicated that privately insured individuals who did not know their coverage status for drug dependence had a lower likelihood of receiving drug treatment from specialty services compared to the uninsured (Cummings et al., 2014). However, Cummings et al. (2014) found alcohol addiction strongly correlated with private insurance use (Cummings et al., 2014). Evidence suggested that many adults remained without health insurance coverage (Allcock et al., 2019; Cummings et al., 2014; Mojtabai et al., 2020; Olfson et al., 2018). According to Cummings et al. (2014), about 25% of adults with alcohol dependence, and 34% of them with drug dependence without insurance coverage. But Choi et al. (2020) noted that older adults were usually covered through Medicare. Health insurance coverage is vital for substance users and expanding health insurance coverage to these populations can help improve their overall health outcomes. The expansion of coverage through the implementation of the Affordable Care Act (ACA) could well achieve this objective (Cummings et al., 2014; Huhn et al., 2020; Mojtabai et al., 2020).

Research Question 3: Health insurance coverage versus treatment completion after controlling for sociodemographic factors.

After sociodemographic factors were adjusted, the results still demonstrated significance between health insurance coverage and treatment completion among participants in this study. The results showed that compared to insured, uninsured 0.733 times less likely [OR=0.733, 95% CI (0.688, 0.781), p<0.0001] to complete treatment. After sociodemographic factors were adjusted, the OR increased from [OR=704] to [OR=0.733]. I concluded an association between health insurance coverage and treatment completion and that employment status and age were confounders on the association.

Limitations of the study

Despite its contribution noted above, the present secondary data analysis and cross-sectional study might have several limitations to be considered. Firstly, data about drug use treatment and coverage were self-reported. This could lead to recall and social desirability biases. Although evidence that TEDS-D datasets have high reliability and validity, it is possible that some respondents might report misleading responses. Drugs are also considered a societal issue and collecting accurate information from individuals dealing with drug use might be challenging. Inaccurate answers to the primary research questions could lead to bias, so it is essential to comprehend the dataset's accuracy being analyzed (Boo & Froelicher, 2013). There was potential for information and selection biases. Cummings et al. (2014) noted that health insurance status is self-reported, and the comprehensiveness of insurance coverage for drug treatment could not be corroborated. Another survey suggested that insurance coverage for substance use treatment depends on the type of services provided at the treatment settings. Understanding insurance coverage for drug abuse can lead a person to seek drug use treatment (Mojtabai et al., 2020). Further, the available datasets did not reveal information related to factors that can influence treatment completion, like existing community resources such as social support (Bazargan-Hejazi et al., 2016). It is imperative to assess the association of insurance coverage with these treatment characteristics in future research.

Secondly, the datasets were derived from submissions by individual programs that received funding from the States. This can hinder data quality collection because agencies receiving less funding might not be able to target and treat many individuals with substance abuse issues as possible. Suntai et al. (2020) noted that only state-funded treatment program outcomes were submitted, which could exclude private treatment programs, private jails, and other programs such as Alcoholics Anonymous (AA). Stahler & Menni (2020) noted that there might be variation in data quality and the way treatment completion was determined at the program level. Therefore, funding restriction might lead to the State's ability to only focus its efforts on the populations at their reach, leaving out many substance abusers without coverage. The available dataset in this study was based on admissions, not individuals. Many survey entries might have been reported as admissions for the same patient instead of the client itself. This could influence the overall outcomes as well as their reliability and validity.

Third, non-responsive and missing information might tilt the direction of the survey and might impact the results. The national TEDS contained many missing values. However, in the final analysis of the extracted Indiana datasets, a simple random sample method had been employed. All missing values were removed during the analysis to minimize the impact of missing values and increase the study outcomes' reliability and validity. Consequently, this study's reliability could be similar to the TEDS-D national survey on substance abuse.

Lastly, the study's cross-sectional nature represents a limitation because data were collected at one specific point in time, and the causality of the association cannot be established. The use of public and de-identified datasets represents a limitation in this study. Evidence showed that the major threats to the reliability and validity of secondary data analysis derived from the approaches used during the initial data collection (Boo &

Froelicher, 2013). Issues may arise from the sampling method used, data collection, non-response, and missing data. Because the researcher did not participate in the initial research design and data collection and because of the nature of this study, the causality of the association between sociodemographic factors and treatment completion as well as the association between health insurance and treatment completion could not fully be assessed (Allcock et al., 2019). It has been demonstrated that the main threats to the reliability and validity of secondary data analysis derived from the accuracy of the approaches used during the primary data collection. However, adequate measures were taken, including sampling strategy and handling of missing data had been employed to minimize potential bias during the analytic phase of this study.

Recommendations

Based on the outcomes of this research, the investigator had formulated various recommendations. First, a statewide longitudinal survey on the association between sociodemographic attributes and treatment completion for opioids abuse should be conducted to recognize the most predictor attributes and develop policies to address the problem. Additionally, a statewide longitudinal survey should be conducted to investigate the association between health insurance coverage and treatment completion for opioids abuse. The state should also enact strict laws to control opioids misuse through medical prescriptions and enforce them rigorously. The state should promote population-based education to increase awareness among those most affected. Interdisciplinary efforts should be fostered by involving all sectors to tackle the ongoing opioids abuse in Indiana and its health consequences, including overdose.

Further, the state must expand health insurance coverage for individuals without coverage for opioids specialty treatment entry through the Affordable Care Act advocacy to improve treatment retention and completion. The federal government must allocate enough funding for states to address this deadly public health issue. The study recommends all healthcare professionals (e.g., physicians, nurses, counselors, and emergency responders) know how to respond to overdose crises to reduce mortality rates. Simultaneously, the integration of substance abuse screening at primary care settings should be among doctors' and nurses' priorities to recognize early signs and initiate referral procedures for immediate care or interventions. Finally, the association of health insurance coverage with treatment completion and the relationship between sociodemographic and opioids abuse need to be explored further to better address this public health issue in the state of Indiana.

Positive social change implications

The study's findings suggested that most of the selected sociodemographic factors (e.g., education, marital status, employment status, gender, race, age) were predictors of opioids abuse in Indiana. Targeting these factors through various intervention plans, including a screening at primary care settings and population-based education, could promote positive social change in Indiana. Special attention should be given to males, minorities, single, full-timers, and older people. Simultaneously, understanding predictors for treatment completion and emphasizing more on full-timers, males, minorities, older people who experienced lower treatment completion rates compared to younger could help develop strategies to improve opioids treatment completion and retention in Indiana.

Also, strengthening and strictly enforcing the existing policies related to opioids prescriptions help promote positive social change in the communities. The study demonstrated that having health insurance coverage was an independent predictor of treatment completion. Hence, expanding insurance health insurance coverage among target populations through Medicaid, Medicare, private, or employers might help improve entry to opioids specialty treatment and promote positive social change among those most affected. Health insurance could be scaled-up through community engagement approaches that employ the media and other advocacy tools.

Conclusion

Opioid abuse remains a pressing public health issue in Indiana. The study suggested marital status, gender, race, and age were the most predictors of opioids abuse in Indiana. It further demonstrated that employment status, gender, and age were most likely to predict successful treatment completion. Finally, people with health insurance coverage had a higher chance of completing treatment than uninsured even after sociodemographic factors were adjusted. Implementing more screening of individuals at risk, promoting population-based education, advocating for health insurance coverage, and enforcing the existing policies vigorously could promote positive social change among the affected communities in Indiana.

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Appendix A: List of Abbreviations

ADOM: Alcohol and DRUG Outcome Measure

AUD: Alcohol use disorder

DALY disability-adjusted life-years

DAWN: Drug Abuse Warning Network

CDC: Centers for Disease Control and Prevention

ISDH: Indiana State Department of Health

YLL: Years of life lost

MC: Marion County

MOUD: Medication for Opioid Use Disorder

MTF: Monitoring the Future

NHAMCS: National Hospital Ambulatory Medical Care Survey

NSDUH: National Survey on Drug Use and Health

NIDA: National Institute on Drug Abuse

NUPO: Nonmedical use of prescription opioids

OPA: Opioid prescription abuse

OPR: Opioid pain reliever

OUD: Opioid use disorder

SCT: Social cognitive theory

UNODC: United Nations Office on Drugs and Crime or UNODC

WHO: World Health Organization

Appendix B: IRB approval number

Your IRB approval number is **11-17-20-0721940**

Appendix C: SPSS Outputs

Education

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Primary	782	3.8	3.8	3.8
	Secondary	4990	24.0	24.0	27.7
	College	4235	20.3	20.3	48.1
	Graduate	586	2.8	2.8	50.9
	High School	10229	49.1	49.1	100.0
	Total	20822	100.0	100.0	

Marital status

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Divorced, widowed	4476	21.5	21.5	21.5
	Separated	284	1.4	1.4	22.9
	Now married	2928	14.1	14.1	36.9
	Never married	13134	63.1	63.1	100.0
	Total	20822	100.0	100.0	

EMPLOY group

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Not in labor force	3398	16.3	16.3	16.3
	Unemployed	8479	40.7	40.7	57.0
	Part-time	2355	11.3	11.3	68.4
	Full-time	6590	31.6	31.6	100.0
	Total	20822	100.0	100.0	

Biologic sex

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	12474	59.9	59.9	59.9
	Female	8348	40.1	40.1	100.0
	Total	20822	100.0	100.0	

Race to group

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Native Americans	80	.4	.4	.4
	Blacks or African Americans	2897	13.9	13.9	14.3
	All Others	1026	4.9	4.9	19.2
	Whites	16819	80.8	80.8	100.0
	Total	20822	100.0	100.0	

AGE Group

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	55 and older	1182	5.7	5.7	5.7
	45-54	3584	17.2	17.2	22.9
	35-44	5200	25.0	25.0	47.9
	18-34	10856	52.1	52.1	100.0
	Total	20822	100.0	100.0	

Health to group

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Uninsured	6926	33.3	33.3	33.3
	Insured	13896	66.7	66.7	100.0
	Total	20822	100.0	100.0	

Other opiates/synthetics reported at admission

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Substance not reported	16686	80.1	80.1	80.1
	Substance reported	4136	19.9	19.9	100.0
	Total	20822	100.0	100.0	

Reason to group

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Treatment not completed	14631	70.3	70.3	70.3
	Treatment completed	6191	29.7	29.7	100.0
	Total	20822	100.0	100.0	

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
Other opiates/synthetics reported at admission * Education	20822	100.0%	0	0.0%	20822	100.0%
Other opiates/synthetics reported at admission * Marital status	20822	100.0%	0	0.0%	20822	100.0%
Other opiates/synthetics reported at admission * EMPLOY group	20822	100.0%	0	0.0%	20822	100.0%
Other opiates/synthetics reported at admission * Biologic sex	20822	100.0%	0	0.0%	20822	100.0%
Other opiates/synthetics reported at admission * Race to group	20822	100.0%	0	0.0%	20822	100.0%
Other opiates/synthetics reported at admission * AGE Group	20822	100.0%	0	0.0%	20822	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	18.028[a]	4	.001
Likelihood Ratio	18.245	4	.001
Linear-by-Linear Association	11.821	1	.001
N of Valid Cases	20822		

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 116.40.

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	.029	.001
	Cramer's V	.029	.001
N of Valid Cases		20822	

Crosstab

			Marital status				
			Divorced, widowed	Separated	Now married	Never married	Total
Other opiates/synthetics reported at admission	Substance not reported	Count	3501	222	2267	10696	16686
		Expected Count	3586.9	227.6	2346.4	10525.1	16686.0
	Substance reported	Count	975	62	661	2438	4136
		Expected Count	889.1	56.4	581.6	2608.9	4136.0
Total		Count	4476	284	2928	13134	20822
		Expected Count	4476.0	284.0	2928.0	13134.0	20822.0

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	38.540[a]	3	.000
Likelihood Ratio	38.092	3	.000
Linear-by-Linear Association	24.908	1	.000
N of Valid Cases	20822		

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 56.41.

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	.043	.000
	Cramer's V	.043	.000
N of Valid Cases		20822	

Crosstab

			EMPLOY group				
			Not in labor force	Unemployed	Part-time	Full-time	Total
Other opiates/synthetics reported at admission	Substance not reported	Count	2716	6610	1926	5434	16686
		Expected Count	2723.0	6794.8	1887.2	5281.0	16686.0
	Substance reported	Count	682	1869	429	1156	4136
		Expected Count	675.0	1684.2	467.8	1309.0	4136.0
Total		Count	3398	8479	2355	6590	20822
		Expected Count	3398.0	8479.0	2355.0	6590.0	20822.0

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	51.717[a]	3	.000
Likelihood Ratio	51.846	3	.000
Linear-by-Linear Association	31.059	1	.000
N of Valid Cases	20822		

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 467.79.

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	.050	.000
	Cramer's V	.050	.000
N of Valid Cases		20822	

Crosstab

			Biologic sex		
			Male	Female	Total
Other opiates/synthetics reported at admission	Substance not reported	Count	10333	6353	16686
		Expected Count	9996.2	6689.8	16686.0
	Substance reported	Count	2141	1995	4136
		Expected Count	2477.8	1658.2	4136.0
Total		Count	12474	8348	20822
		Expected Count	12474.0	8348.0	20822.0

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	142.480[a]	1	.000		
Continuity Correction[b]	142.058	1	.000		
Likelihood Ratio	140.663	1	.000		
Fisher's Exact Test				.000	.000
Linear-by-Linear Association	142.473	1	.000		
N of Valid Cases	20822				

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 1658.21.

b. Computed only for a 2x2 table

Crosstab

			Race to group				
			Native Americans	Blacks or African Americans	All Others	Whites	Total
Other opiates/synthetics reported at admission	Substance not reported	Count	73	2743	872	12998	16686
		Expected Count	64.1	2321.6	822.2	13478.1	16686.0
	Substance reported	Count	7	154	154	3821	4136
		Expected Count	15.9	575.4	203.8	3340.9	4136.0
Total		Count	80	2897	1026	16819	20822
		Expected Count	80.0	2897.0	1026.0	16819.0	20822.0

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	492.672[a]	3	.000
Likelihood Ratio	616.124	3	.000
Linear-by-Linear Association	485.341	1	.000
N of Valid Cases	20822		

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 15.89.

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	.154	.000
	Cramer's V	.154	.000
N of Valid Cases		20822	

Crosstab

			AGE Group				
			55 and older	45-54	35-44	18-34	Total
Other opiates/synthetics reported at admission	Substance not reported	Count	1076	3157	4141	8312	16686
		Expected Count	947.2	2872.1	4167.1	8699.6	16686.0
	Substance reported	Count	106	427	1059	2544	4136
		Expected Count	234.8	711.9	1032.9	2156.4	4136.0
Total		Count	1182	3584	5200	10856	20822
		Expected Count	1182.0	3584.0	5200.0	10856.0	20822.0

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	318.205[a]	3	.000
Likelihood Ratio	350.593	3	.000
Linear-by-Linear Association	301.720	1	.000
N of Valid Cases	20822		

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 234.79.

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	.124	.000
	Cramer's V	.124	.000
N of Valid Cases		20822	

Reason to group[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B) Lower Bound	Upper Bound
Treatment not completed	Intercept	.982	.019	2657.389	1	.000			
	[Health to group=0]	-.351	.032	123.219	1	.000	.704	.662	.749
	[Health to group=1]	0[b]	.	.	0	.	.	.	.

Case Processing Summary

		N	Marginal Percentage
Reason to group	Treatment not completed	14631	70.3%
	Treatment completed	6191	29.7%
Health to group	Uninsured	6926	33.3%
	Insured	13896	66.7%
Education	Primary	782	3.8%
	Secondary	4990	24.0%
	College	4235	20.3%
	Graduate	586	2.8%
	High School	10229	49.1%
Marital status	Divorced, widowed	4476	21.5%
	Separated	284	1.4%
	Now married	2928	14.1%
	Never married	13134	63.1%
EMPLOY group	Not in labor force	3398	16.3%
	Unemployed	8479	40.7%
	Part-time	2355	11.3%
	Full-time	6590	31.6%
Biologic sex	Male	12474	59.9%
	Female	8348	40.1%
Race to group	Native Americans	80	0.4%
	Blacks or African Americans	2897	13.9%
	All Others	1026	4.9%
	Whites	16819	80.8%
AGE Group	55 and older	1182	5.7%
	45-54	3584	17.2%
	35-44	5200	25.0%
	18-34	10856	52.1%
Valid		20822	100.0%
Missing		0	
Total		20822	
Subpopulation		1878[a]	

a. The dependent variable has only one value observed in 930 (49.5%) subpopulations.

Parameter Estimates

Reason to group[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B) Lower Bound	Upper Bound
Treatment not completed	Intercept	.712	.043	277.116	1	.000			
	[Health to group=0]	-.325	.033	99.701	1	.000	.722	.678	.770
	[Health to group=1]	0[b]	.	.	0	.	.	.	.
	[Education=1]	.150	.087	3.007	1	.083	1.162	.981	1.378
	[Education=2]	.068	.039	2.990	1	.084	1.070	.991	1.155
	[Education=3]	-.089	.040	4.835	1	.028	.915	.846	.990
	[Education=4]	-.302	.090	11.371	1	.001	.739	.620	.881
	[Education=5]	0[b]	.	.	0	.	.	.	.
	[Marital status=1]	.131	.040	10.502	1	.001	1.140	1.053	1.234
	[Marital status=2]	-.019	.133	.020	1	.888	.982	.757	1.273
	[Marital status=3]	-.008	.045	.030	1	.863	.992	.908	1.084
	[Marital status=4]	0[b]	.	.	0	.	.	.	.
	[EMPLOY group=1]	.657	.050	171.441	1	.000	1.929	1.748	2.128
	[EMPLOY group=2]	.588	.036	261.582	1	.000	1.801	1.677	1.934
	[EMPLOY group=3]	.331	.052	39.910	1	.000	1.392	1.256	1.542
	[EMPLOY group=4]	0[b]	.	.	0	.	.	.	.
	[Biologic sex=1]	-.049	.033	2.237	1	.135	.952	.893	1.015
	[Biologic sex=2]	0[b]	.	.	0	.	.	.	.

	[Race to group=1]	-.213	.239	.795	1	.373	.808	.506	1.291
	[Race to group=2]	.061	.046	1.778	1	.182	1.063	.972	1.162
	[Race to group=3]	-.148	.070	4.472	1	.034	.863	.753	.989
	[Race to group=4]	0[b]	.	.	0	.	.	.	.
	[AGE Group=1]	-.676	.069	96.930	1	.000	.509	.445	.582
	[AGE Group=2]	-.191	.043	19.408	1	.000	.826	.759	.899
	[AGE Group=3]	-.093	.039	5.789	1	.016	.911	.845	.983
	[AGE Group=4]	0[b]	.	.	0	.	.	.	.

a. The reference category is: Treatment completed.

b. This parameter is set to zero because it is redundant.