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Factors Associated With Nonmedical Prescription Opioid Use and Prescription Opioid Misuse Among Rural Americans

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This is to certify that the doctoral dissertation by

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Walden University
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Abstract

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Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

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Abstract

Opioid misuse is a rapidly evolving health epidemic in the United States, leading to opioid use disorders, overdose deaths, and disparities in treatment. The rural population may be more susceptible given socioeconomic status, less educational attainment, and lower income. The impact on specific populations is not well understood. The purpose of this study was to identify the association of nonmedical prescription opioid use (NPOU), prescription opioid misuse (POM), and treatment-seeking with race, age, sex, education, and insurance status among rural Americans. The social-ecological model (SEM) served as the theoretical framework. The SEM described the interplay between individual, relationship, community, and societal elements. A quantitative approach was used to analyze data from the 2019 National Survey on Drug Use and Health. Multiple logistic regression models were used to examine associations between the potential risk factors and the opioid-related outcome variables noted above among rural Americans. Results revealed that Black race, age, education, and health insurance coverage were important predictors of NPOU. Black race and younger age were predictors of POM. Finally, younger age, male sex, and persons with lower levels of education were predictors of treatment-seeking. Social change could result from implementing policies based on this study to ensure equitable practices for this vulnerable population, preventing opioid misuse and increasing access to treatment.

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Dedication

This research study is dedicated to my supportive husband, Jarred A. Cox, who has served as my biggest cheerleader throughout this entire process. This research is also dedicated to my mother, Cheryl L. Alston, who instilled in me a deep appreciation for education, and whose sacrifices afforded me the opportunities I have today. Finally, this research is dedicated to the rural populations I am privileged to serve in a public health capacity each day.

Acknowledgments

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Chapter 1: Introduction to the Study

Opioids are a class of medication used for pain reduction and management when other drugs prove insufficient (Healthline, 2019). Because opioids suppress the transmission of the body's signal for pain to the brain, they effectively manage more severe levels of pain (Johns Hopkins Medicine, 2020). The U.S. Department of Health and Human Services (2019) National Survey on Drug Use and Health (NSDUH) defined nonmedical prescription opioid use (NPOU) as the use of a prescription opioid not prescribed or taken for the experience or feeling it may cause. The volume of opioid prescriptions has increased exponentially over the past 2decades. According to the Centers for Disease Control and Prevention (CDC, 2019), physicians prescribed opioids at a rate three times greater per person in 2019 than in 1999.The increase in access to opioid prescriptions has led to a growing prevalence of prescription opioid misuse (POM), which entails using a prescribed opioid in any way other than intended by the prescriber (National Institute on Drug Abuse [NIDA], 2019). Approximately one quarter of patients misuse opioids prescribed to them for chronic pain reduction, according to the National Center for Drug Abuse Statistics (2019). Those residing in rural communities may be especially susceptible to NPOU and POM given higher rates of factors closely associated with NPOU and POM, namely, lower educational attainment and lower income (Rigg & Monnat, 2015).

The findings of this study provide useful information for public health practitioners and policymakers regarding the magnitude of the opioid problem in the rural community, as well as which sociodemographic groups are at greatest need for targeted intervention strategies to minimize the occurrence of NPOU and POM and to enhance access to treatment for opioid addiction. In Chapter 1, I will discuss the background of NPOU, POM, and treatment-seeking behaviors for opioid addiction among rural residents. I will demonstrate that POM among rural populations is a significant public health problem. The variables, including independent, dependent, and covariates, will be described. Also included in this chapter are the research questions and the null and alternative hypotheses specifying the variables and their association of study. Next, I will discuss the social-ecological model (SEM), which served as the theoretical framework for the study. The nature of the study will then be addressed, including the rationale for the study design and how the data were collected and analyzed. I will also provide a discussion of terms used in this study, followed by the assumptions and limitations of the research. Finally, I will present a discussion of the significance of the study, including potential contributions of the study to the literature and social change.

Background

In this section, I provide a summary of the research literature in regard to NPOU, POM, and treatment-seeking behavior. I identify a gap in the literature that my study addressed. I also address why this study is necessary.

As I discussed above, the increase in opioid prescriptions over the past 2decades has led to a growing prevalence of misuse of prescription opioids. The misuse of prescription opioids is a national issue with serious implications for public health and an economic burden with an estimated cost of $78.5 billion a year in the United States (CDC, 2019; NIDA, 2020). The consequences of NPOU and POM can be as severe as death. According to Rigg and Nicholson (2019), a third of the deaths caused by overdose in 2015 were due to prescription opioids. Prescription opioids are responsible for more annual deaths than heroin and cocaine combined (Rigg & Monnat, 2015). Additional outcomes of POM include behavioral health disorders, costing the United States an estimated $420 billion annually (Ashford et al., 2018), The rate of prescription opioid use and misuse varies between rural and urban populations, with rural communities often lacking the resources available to their urban counterparts. Misuse of OxyContin, one of the most common opioids, first appeared in rural areas, such as those in Maine, western Virginia, southern Ohio, and eastern Kentucky, initiating the current epidemic (Rigg & Monnat, 2015). High rates of POM were found in rural populations; for example, rural Kentucky communities showed more use of oxycodone and hydrocodone than urban areas of the state (Rigg & Monnat, 2015).

Identifying demographic factors that impact rural and urban differences of NPOU and POM is critical when developing targeted interventions to address individuals' distinct needs in these areas (Rigg & Monnat, 2015). In this study, I examined whether race, age, sex, education, and insurance status are associated with NPOU, POM, and treatment-seeking patterns among the rural population. Fully gauging the future influence of POM intervention and effective opioid treatment programs requires considering the differences in opioid use (Pouget et al., 2018).

Despite data showing differences in the rates of NPOU and POM based on patient characteristics, the impact on specific populations is not well understood. Rural communities may be especially susceptible. According to the CDC (2015), opioid-related overdoses are 45% more prevalent in rural counties than metropolitan counties. The rural community is sensitive to opioid use due to economic distress, poor housing, and poverty (Toliver, 2016). According to Toliver (2016), rural occupations are highly susceptible to physical injuries, which introduces access to opioid prescriptions. A large number of older rural residents may present to their primary care providers with chronic health issues that require an opioid prescription (Toliver, 2016). We do not know the association of various factors for NPOU, POM, and treatment-seeking among the rural population. This study specifically focused on the following factors: racial disparities, age, gender, educational attainment, and insurance status. Rural communities are often isolated from addiction counseling and treatment facilities, resulting in high rates of recidivism of substance use among the rural population (Tolliver, 2016)

The most successful course of action for treating opioid use disorder is the use of long-term pharmacotherapy, which improves physical and mental health and social functioning, relapse prevention, and mortality reduction (Muthuligam et al., 2019). Various treatment options are required to address the unique needs of each patient. Treatment options include extended-release naltrexone, injectable buprenorphine administered monthly subcutaneously, surgically implanted buprenorphine that lasts for 6 months, sublingual buprenorphine available for purchase at the local pharmacy for daily at-home administration, and methadone taken orally and daily at a licensed treatment center (Muthuligam et al., 2019). Notwithstanding various treatment options, less than 11% of individuals with opioid use disorder receive treatment (Muthuligam et al., 2019). In addition, individuals with access to treatment often do not take advantage of these services. It is critical to examine the individual-level and systemic barriers to seeking treatment to increase treatment access, especially for the more vulnerable populations.

Treatment programs for opioid misuse have shown to be effective; however, access to treatment is often a challenge. Potential barriers to seeking treatment for NPOU and POM among rural populations have not been well studied, however. A research focus on the rural community would add to the literature.

Problem Statement

The volume of opioid prescriptions has grown exponentially over the past 2decades. According to the CDC (2019), physicians prescribed opioids to three times as many people in 2019 than in 1999. Additionally, this increase in access to prescription opioids has led to a higher prevalence of NPOU and POM. Approximately one quarter of patients misuse opioids prescribed to them for chronic pain reduction, according to the National Center for Drug Abuse Statistics (2019). This is a significant public health problem because it has potential implications on social structure, criminal activity, and affects both the individual as well as the overall community.

Despite data to suggest differences in rates of NPOU and POM based on patient characteristics, the impact on specific populations is not well understood. As discussed above, individuals residing in rural communities may be especially susceptible to NPOU and POM given higher rates of factors closely associated with NPOU and POM—specifically, lower educational attainment and income (Rigg & Monnat, 2015).

Although treatment has proven highly effective in reducing recidivism for substance misuse, affordable treatment within the rural community can be difficult to obtain. According to the U.S. Census Bureau (2019), 12.3% of rural counties are uninsured compared to 10.1% of urban counties. High percentages of rural county residents take advantage of public health insurance and are limited by the fact that public health insurance is not accepted by many private substance abuse treatment programs (James &Jordan, 2018). For those individuals who do seek treatment, immediate availability is not guaranteed, are often placed on a waiting list, and are more likely to revert back to substance use (Toliver, 2016). The intention may be present; however, it is imperative that barriers to treatment-seeking be fully explored in order to effectively address them.

Purpose of the Study

The purpose of this quantitative study was to identify sociodemographic factors associated with NPOU, POM, and treatment-seeking among the rural population. Regarding sociodemographic factors, race has proven to be a significant factor in urban populations, with African Americans being more likely to experience opioid addiction and have less access to treatment for opioid dependency than European Americans (James & Jordan, 2018). This study was a means to determine whether race is a significant factor among the rural population. Also assessed were other sociodemographic factors shown to contribute to POM and NPOU outcomes, including age, sex, and socioeconomic status (i.e., education and insurance; Rigg & Nicholson, 2019). Gaining an understanding of the factors associated with NPOU, POM, and access to treatment for opioid addiction among rural populations can potentially aid in developing targeted interventions for preventing misuse and increasing access to treatment.

Research Questions and Hypotheses

This study was an examination of three research questions and their corresponding hypotheses.

RQ1: What sociodemographic factors (race, age, sex, education, and insurance status) are independently associated with NPOU among rural Americans after adjusting for the other sociodemographic factors?

For each sociodemographic factor, the null and alternative hypotheses are:

$H_0$1: The given sociodemographic factor is not independently associated with NPOU among rural Americans.

H_a1: The given sociodemographic factor is independently associated with NPOU among rural Americans.

RQ2: What sociodemographic factors (race, age, sex, education, and insurance status) are independently associated with POM among rural Americans after adjusting for the other sociodemographic factors?

For each sociodemographic factor, the null and alternative hypotheses are:

$H_0$2: The given sociodemographic factor is not independently associated with POM among rural Americans.

H_a2: The given sociodemographic factor is independently associated with prescription opioid misuse among rural Americans.

RQ3: Among rural Americans who have misused prescription opioids, what sociodemographic factors (race, age, sex, education, and insurance status) are independently associated with seeking treatment after adjusting for the other sociodemographic factors?

For each sociodemographic factor, the null and alternative hypotheses are:

$H_0$3: Among rural Americans who have misused prescription opioids, the sociodemographic factor is not independently associated with seeking treatment.

H_a3: Among rural Americans who have misused prescription opioids, the sociodemographic factor is independently associated with seeking treatment.

Theoretical Framework for the Study

Bronfenbrenner's (1979) SEM provided the framework to identify factors that influence opioid misuse and potential preventive measures. Initially Bronfenbrenner developed this theory based on the premise of systems thinking, postulating that it is critical to gain an understanding of the ecological system as a whole in order to fully understand human development (Susser & Susser, 1996). This model was created to allow researchers to take into consideration the complexities that must interact across the individual, relationship, community, and societal levels of the model (CDC, 2020). Researchers can also observe potential prevention strategies with the assistance of the SEM. A more detailed discussion of the model appears in Chapter 2. This study's focus was opioid misuse at the societal level, highlighting factors that create an environment conducive for opioid misuse. Cultural and societal norms and contributing factors to health inequities among the rural population were considerations at the societal level, including overprescribing by clinicians, inadequate security to recognize opioid abuse, and the lack of policies to provide individuals with the help they need.

Nature of the Study

The nature of the study is quantitative methodology with a cross-sectional design. This study was quantitative because I gathered secondary data and performed a statistical analysis to describe the study population and examine relationships between variables, as described below. The analysis permitted me to make generalizations about the rural population under study. A cross-sectional design was used because the study observed a single point of data collection for each respondent. I examined the relationship between predictor variables (i.e., sociodemographic factors, including race, age, sex, education, and insurance status) with outcome variables of NPOU, POM, and treatment-seeking for opioid misuse among rural communities. I used quantifiable data from the NSDUH to measure factors from a specific period from reported cases of NPOU and POM. Data were obtained for the 2019 NSDUH from 50 states and the District of Columbia using an independent, multistage area probability random sample of the United States. Thus, this sample is representative of the entire nation. The target population for this study is the rural population, household residents, ages 12 and older. Survey administration was via computer-assisted personal interviews and audio self-interviews. As the outcomes for this study are binary, multiple logistic regression models are appropriate for analyzing data. The rationale for using the logistic regression model includes that a binary dependent variable, independence of observations, independent variables linearly related to the log odds, absence of multicollinearity, and no outliers (Statistics Solutions, 2021). Thus, the

Hosmer-Lemeshow goodness of fit statistic (Real Statistics, 2020) was appropriate to assess the variables and the fit of the final models for each research question.

Definitions

I provide definitions for the variables to be analyzed in this study. More detailed analysis of coding and how these variables were characterized and analyzed will be described in Chapter 3.

Education: Education is the enhancement and development of human potential, integrity, identity, consciousness, and ability (Jootaek, 2020). The data used for this study are from the 2018 NSDUH. The survey provides reports based on four categories of education level: less than a high school education, high school graduate, some college/associate degree, and college graduate.

Insurance status: Private insurance is health care coverage obtained through an employer, a union, or a professional association (NSDUH, 2019). Individuals pay premiums based on a plan purchased through the Healthcare Marketplace or directly to a health insurance company. For this study, private insurance included a health maintenance organization, single-service plan, or fee-for-service plan. The survey reported if the respondent’s insurance covered drug abuse treatment and if the respondent had health insurance coverage over the 12 months before taking the survey.

Nonmedical prescription opioid use: According to the U.S. Department of Health and Human Services (2019) NSDUH, NPOU is the use of a prescription opioid not prescribed or taken for the experience or feeling it may cause. In the United States, NPOU doubled over the 10years between 2002 and 2012 (National Institutes of Health

[NIH], 2016). More than 11% of the American adult population reported NPOU within their lifetime, which was accompanied by a greater prevalence of morbidity and mortality (NIH, 2016).

Opioid: Opioids are a class of medication used for severe levels of pain reduction and management by suppressing the transmission of the body's pain signal to the brain (Healthline, 2019; Johns Hopkins Medicine, 2020). In addition to pain relief, opioids produce a euphoric experience, and consistent use can result in dependence (NIDA, 2019). Approximately 70% of all drug overdose deaths reported in 2018 were attributed to opioid use (CDC, 2020). This drug classification includes fentanyl, heroin, and prescription opioids.

Overdose death: The age-adjusted rate of U.S. overdose deaths in 2018 was 20.7 per 100,000 individuals (CDC, 2020). Two of three opioid overdose deaths are caused by synthetic opioids, such as fentanyl. In 2018, opioids caused 69.5% of overdose deaths.

Overdose: An overdose entails ingesting a toxic level of a drug that prohibits the human body's normal function (American Addiction Centers, 2022). Whether fatal or nonfatal, an overdose entails poisoning the body by introducing excessive amounts of a drug (CDC, 2020). In 2017, approximately 48,000 individuals died from opioid overdose in the United States (Ahmedani et al., 2020).

Prescription opioid misuse (POM): Increased access to opioid prescriptions has led to a growing prevalence of POM, which entails using a prescribed opioid in any way other than intended by the prescriber (NIDA, 2019). Misuse can include taking a higher dose than prescribed or taking an opioid prescribed for someone else. POM accounts for more than 16,000 American deaths each year and costs $56 billion annually (Rigg & Monnat, 2015).

Prescription opioid: Medically prescribed opioids for chronic pain from a surgical procedure, injury, or cancer (CDC, 2017). In 2017, U.S. patients filled more than 191 million opioid prescriptions (CDC, 2017), including morphine, methadone, codeine, hydrocodone (Vicodin), and oxycodone (OxyContin; NIDA, 2019). Repeated nonmedical use or misuse of a prescription opioid can result in an opioid use disorder where changes to the brain cause severe health issues (NIDA, 2019).

Race and ethnicity: Race is based on self-identified social groups, including White, Black/African American, Asian, American Indian/Alaska Native, and Native Hawaiian/Pacific Islanders (U.S. Census Bureau, 2020). Some individuals may identify with more than one social group. Ethnicity is an individual's self-identified nationality, language, culture, religion, geography, or family origin. In this study, the 2019 NSDUH respondents were asked to identify themselves as either Non-Hispanic White, Non-Hispanic Black/African American, Non-Hispanic Native American/Alaska Native, Non-Hispanic Native Hawaiian/Pacific Islander, Non-Hispanic Asian, Non-Hispanic more than one race, or Hispanic.

Treatment: Several approaches are available to treat drug misuse and prevent relapse, including medication and behavioral counseling (NIDA, 2019). Treatment is adaptable to the unique needs of each patient. The most effective treatment is a comprehensive program with both mental health and medical services. Medication-assisted treatment often includes providing naltrexone, buprenorphine, and methadone in combination with counseling and therapy (CDC, 2019).

Treatment-seeking: Treatment-seeking is the pursuit of remediation for a mental or physical illness, instability, or disturbance (Pam, 2013). In the first year of a substance use disorder, treatment-seeking rates are higher for drug dependence than alcohol dependence (Blanco et al., 2015). Having a prior history of receiving treatment for substance use disorder is an indicator of treatment-seeking for another substance use disorder (Blanco et al., 2015). Comorbidities can either increase or decrease the probability of seeking treatment (Blanco et al., 2015).

Assumptions

As the NSDUH sample is based upon a randomized, probability sample of the United States, I assume that the sample is nationally representative and accurately reflects the US rural population. Using a population-based dataset ensures the external validity of the study. The NSDUH has been conducted annually since 1990 and obtains information in regard to tobacco, alcohol, and drug use, in addition to alcohol and drug dependence, misuse, abuse, and treatment and mental health from approximately 70,000 individuals 12 years of age or older (Substance Abuse and Mental Health Data Archive [SAMHDA],2019). I assumed that the respondents are providing accurate and honest responses. These assumptions are reasonable because the NSDUH ensures a valid sample, anonymous interviews, and confidentiality. The modes for administering the survey include audio computer-assisted personal interviews and audio self-interviews which maintains privacy and confidentiality for responses which address sensitive topics (SAMHDA,2019).

Scope and Delimitations

The scope of this study is based upon rural residents aged 12 years and older in the United States. I am focusing on this population given the lack of previous research for these individuals with regard to NPOU, POM, and treatment-seeking behaviors. The data I used are from 2019. I did not examine trends over time.

Delimitations are boundaries specifically set by the researcher that limit the scope of a study. The researcher attains delimitation by instituting parameters of the location and participants of the study (Bloomberg & Volpe, 2012; Kirkwood & Price, 2013). This study included people 12 years and older located in rural communities in the United States who (a) have participated in NPOU in the last 12 months, (b) have participated in POM in the last 12 months, and (c) have participated in POM and sought a treatment program with in the last 12 months. These criteria were prioritized because they support the research of factors that influence NPOU, POM, and treatment-seeking among rural residents aged 12 years or older in the United States. The study was delimited to rural residents aged 12 years or older who have participated in NPOU or POM and those who participated in POM and sought treatment. The chosen theoretical framework was the SEM. Researchers who have utilized the SEM were able to take into consideration the complexities that must interact across the individual, relationship, community, and societal levels of the model (CDC, 2020).

As previously discussed, the NSDUH sample is based upon a randomized, probability sample of the United States, so I assumed that the sample is nationally representative and accurately reflects the U.S. rural population. The study is delimited to rural residents. Therefore, the findings of this study will be generalizable to rural populations within the United States.

Limitations

A study's limitations are elements of the methodology or design that could influence the findings, affecting generalizability, application, and utilization and the ability to establish internal and external validity (University of Southern California, 2020). A potential limitation in this study is the use of secondary data. The NSDUH is a comprehensive secondary dataset. The survey employs an audio computer-assisted self-interviewing process. Respondents reserve the right not to provide a response for each survey question. This can lead to missing data. Missing data from the original survey could reduce the reliability of results and skew inferences. The NSDUH had checks in place to reduce missingness. The NSDUH utilizes imputation to address missing data. SAMHDA (2019), defines imputation as replacing missing values with valid values. Statistical imputation was implemented to derive an estimated value for the missing value from the available values provided by the respondent. By the time I finished my research, the data may no longer have been relevant due to the constant changes that take place within this field of study. The data come from a survey of a randomized household sample. SAMHDA (2019) defined a household as civilian noninstitutionalized residence (including civilians residing on a military base, college dormitories, group homes, homeless people in shelters, and long-term residents of single rooms in hotels). A household sample may not be representative of substance users who experience housing instability. The data are also self-reported, which could have introduced response bias, underestimation, or overestimation (Lavrakas, 2008). In addition, respondents might not be fully forthcoming, especially given the sensitive topics that the survey addresses. The survey creators addressed this limitation by ensuring confidentiality by implementing an audio computer-assisted self-interviewing process. Variables of interest not used in this study could have contributed to internal validity and indicated cause and effect. Regardless of these limitations, findings could contribute to the current literature regarding NPOU, POM, and treatment-seeking behaviors among the rural community.

Significance

The purpose of this study was to determine the association between NPOU, POM, and treatment-seeking among the rural population, controlling for race, sex, age, education, and insurance status. This study is significant because it can contribute several outcomes. This study is aimed at increasing education and awareness of NPOU, POM, and treatment-seeking. In addition, this study could expand education and awareness of sociodemographic factors that contribute to NPOU, POM, and treatment-seeking among the rural population. It has potential implications for positive social change within the rural community and public health regarding research, practice, and policy. The findings will provide information to help communities understand the impact of NPOU, POM, and treatment-seeking behavior within the rural population. Policies developed based on the study could ensure equitable practices for this vulnerable population by preventing opioid misuse and increase access to treatment. Health care providers and pharmacies can assist with the implementation of these policies. Finally, more targeted interventions could help increase treatment-seeking rates and decrease rates of NPOU and POM overdose deaths among the rural population.

Summary

In Chapter 1, I provided a detailed discussion of NPOU, POM, and treatment-seeking and the literature regarding the rural population. I also presented the purpose of the study, research questions and hypotheses, theoretical framework, nature of the study, definitions, assumptions, limitations, and the significance of the study. I concluded the chapter with a description of the implications for positive social change. In Chapter 2, I will present the literature search strategy, theoretical foundation, and literature review related to key variables and concepts.

Chapter 2: Literature Review

The volume of opioid prescriptions has grown exponentially over the past 2decades. The U.S. Department of Health and Human Services (2019) NSDUH defined NPOU as use of a prescription opioid not prescribed, or taken for the experience or feeling it may cause. Additionally, the increase in access to opioid prescriptions has led to a growing prevalence of POM, which entails the use of a prescribed opioid in any way other than intended by the prescriber (NIDA, 2019).

Although data exist to suggest that there are differences in rates of NPOU and POM based upon patient characteristics, the impact on certain populations is not well understood. Those residing in rural communities may be especially susceptible to NPOU and POM given higher rates of factors closely associated with NPOU and POM, namely, lower educational attainment, and lower income (Rigg & Monnat, 2015).

Though treatment programs for opioid misuse have been shown to be effective, access to treatment is often challenging. Of those living with opioid use disorders, 80% do not receive treatment (Partnership to End Addiction, 2015). The potential barriers to seeking treatment for NPOU and POM among the rural population have not been well studied, however.

The purpose of this study was to identify sociodemographic factors associated with NPOU, POM, and treatment-seeking among the rural population. This study identified whether race is a significant factor among the rural population. Other sociodemographic factors, namely age and sex, as well as measures of socioeconomic status (i.e., education and insurance status) that have also been shown to be related to the aforementioned opioid-related outcomes (Rigg &Nicholson, 2019), were assessed. The rural population faces unique barriers to seeking POM treatment due in large part to having limited resources. Gaining an understanding of the factors that are associated with NPOU, POM, and access to treatment, among the rural-residence population can potentially aid in developing targeted interventions for preventing misuse and increasing access to treatment for this vulnerable population.

Identifying factors that contribute to NPOU and POM among the rural population could help to improve the overall health of this population. Individuals residing in rural communities are especially susceptible relative to their urban counterparts, given the increased factors closely associated with NPOU and POM, such as lower educational attainment and lower income (Rigg & Monnat, 2015). These factors indicate the need for mitigation strategies to effectively address this public health issue.

I include in this chapter an in-depth exploration of the factors associated with NPOU, POM, and treatment-seeking among the rural population. Specifically, I discuss the strategy for searching the literature to inform this research project, the theoretical foundation for this study, and a detailed review of the relevant literature related to the variables I examined. I conclude Chapter 2 with a summary section and a preview of Chapter 3.

Literature Search Strategy

For this literature review, I employed a strategy that entailed an exhaustive overview of electronic databases. I obtained the literature for review by using the databases CINAHL, MEDLINE, PsycINFO, ScienceDirect, ProQuest, SAGE, EBSCOHost, and ERIC. Search strategy combinations of key search terms included

- *opioids OR opiates OR pain medication OR morphine OR oxycodone OR oxycontin*
- *AND misuse OR abuse OR addiction*
- *AND rural OR regional OR remote OR non-urban*
- AND *race* OR *age* OR *sex* OR *education* OR *insurance status*

This database search returned 739 articles from peer-reviewed journals. Although the publication dates of the primary sources were between 2015 and 2020, older material was acceptable for seminal articles and the theoretical foundation.

Theoretical Foundation

The SEM (see Figure 1) provides the theoretical framework for this study. Bronfenbrenner developed the SEM in 1979 to describe the interplay between individual, relationship, community, and societal elements. The following paragraphs present each level of the SEM.

Figure 1

Social-Ecological Model

Note. Adapted from *The Social-Ecological Model: A Framework for Prevention,* by Centers for Disease Control and Prevention, 2020 (https://www.cdc.gov/violenceprevention/about/social-ecologicalmodel.html). In the public domain.

The first level of the SEM, the individual, refers to biology and the unique, personal experiences that result in a particular behavior, such as NPOU or POM (CDC, 2020). Influential components at the individual level include age, education attainment, income, and substance use. Preventative measures at this stage focus on behaviors, attitudes, and beliefs. Addressing NPOU and POM at the individual level would entail matching the individual with a treatment program.

The second level of the SEM is relationship, which pertains to a person's most intimate social groups, peers, family, and partners to identify how these connections impact the individual's behavior (CDC, 2020). Any NPOU and POM prevention at this level would be the most effective by addressing the support system as a whole.

The third level of the SEM is the community, comprising the environment in which individuals cultivate relationships, such as the school, workplace, or neighborhood (CDC, 2020). The SEM incorporates the components of the community that are conducive for specific behaviors, such as NPOU and POM. An intervention at the third level would target the community as a whole, where policy change can prove most beneficial.

Finally, the fourth level of the SEM is societal, at which level an individual examines behavior through a systematic lens. At the forefront of the societal level, cultural norms lead to behaviors, such as NPOU and POM, as a coping mechanism. Societal components involve policies that support economic, resource, and social disparities (CDC, 2020). Examples of societal factors include overprescribing by clinicians, inadequate ability to recognize opioid misuse, and a lack of policies to ensure treatment for individuals in need.

The SEM has been a frequent factor in studies surrounding NPOU and POM. Researchers have focused on the individual and the unique risks regarding personal experiences (Jalali et al., 2020). Jalali et al. (2020) proposed a social-ecological framework to assist with the multivariable risk factors associated with opioid misuse, guiding a public health approach for analysis at the individual, relationship, community, and societal levels. The researchers’ work suggests that an issue as complex as the opioid crisis demands a comprehensive mitigation strategy to develop effective treatments and preventive measures.

Tran et al. (2012) used the SEM to identify variations in opioid use sequences and multilevel projections of continuous opioid use during treatment. The findings indicated that, at the individual level, a history of opioid use and relapse were positively associated with continued opioid use. This study showed the significance of the social component in the effectiveness of addiction treatment. Patients identified as having family and social instability status and experiencing peer pressure were at higher risk for continued opioid use. Protective factors against opioid use at the relationship and community levels included social integration, marriage, peer education, and access to health care.

According to Thompson et al. (2020), identifying multilevel contextual influencers of opioid use could be beneficial for the development of future public health interventions. Their study brought attention to several contextual themes concerning opioid use. At the relationship level of the SEM, peers and family greatly influenced the denial and acceptance of opioid use. At the community level, impacts on behaviors came from community environment, social norms, economic shifts, community leadership, availability of treatment programs, and economic disadvantage.

The SEM is a useful framework that aids in developing targeted interventions for preventing NPOU and POM and increasing access to treatment for the rural population. Sociodemographic factors that influence opioid misuse and potential preventive measures were identifiable through the lens of this model. This study's focus was on opioid misuse at the societal level, highlighting the sociodemographic factors of race, age, sex, education, and insurance status that facilitate an environment conducive for opioid misuse and barriers to treatment-seeking among the rural population. Cultural and societal norms and contributing factors to health inequities among the rural community were considerations at the societal level of this framework.

Literature Review Related to Key Variables and Concepts

Constructs of Interest

In the following subsections, I discuss the constructs of interest in this study, which include opioid use disorder, opioid use disorder treatment, overdose deaths, and rural disparities.

Opioid Use Disorder and Opioid Use Disorder Treatment

It is critical to identify which demographic factors contribute to opioid use disorder and treatment-seeking in order to target effective interventions. Ahmedani et al. (2020) conducted an observational study to identify the prevalence of opioid use disorder and opioid use disorder treatment among primary care patients. The researchers defined opioid use disorder treatment as a prescription for buprenorphine for opioid use disorder. Data were obtained from electronic health records over a 3-year period (2013–2016) for adult patients with two or more primary care visits. The study adjusted for health system, race/ethnicity, gender, and age for the prevalence of opioid use disorder. The chosen methodology for the study was a logistic regression. Ahmedani et al.'s approach revealed that the prevalence of treatment varied across demographic factors for patients who had an opioid use disorder. Their findings constitute systems-level changes to increase opioid use disorder treatment.

Equitable treatment should be accessible for all populations. Stein et al. (2018) developed a research study to highlight whether the approval of medication treatment for opioid use disorders derived an increase in individuals receiving medication treatment and whether receipt of treatment was fair across communities. Individuals were defined as receiving treatment with methadone if they possessed a claim at an opioid treatment program within a year. Individuals were defined as receiving treatment with buprenorphine if they filled a prescription for buprenorphine within a year. Individuals were defined as receiving medical treatment if they were treated with methadone or buprenorphine within a year. When a county possessed a poverty rate above the federal poverty line it was labeled as a high poverty community. The authors of this study used multiple logistic regression models. Stein et al. found an increase in receipt of treatment among Medicaid-enrollees. They also revealed that treatment proved disproportionate based on the traits of the county population. This was especially true among counties historically disadvantaged in regard to access to quality care. In 2017, approximately 48,000 individuals suffered opioid overdose deaths in the United States (Ahmedani et al., 2020).

Overdose Deaths

Lives lost to opioid overdose increased fourfold between 1999 and 2011 (Kumari et al., 2016). It is critical to combat opioid misuse and prevent overdose deaths. In the United States, there were more than 100 opioid overdose deaths daily in 2016 (Kumari et al., 2016). Lippold et al. (2019) noted that racial/ethnic differences in opioid overdose deaths varied according to urban–rural residence. Saloner et al. (2018) designated opioid overdose as the leading cause of injury death in the United States.

Lippold et al. (2019) proposed a multifaceted response to the opioid crisis at the local, state, and national levels, addressing racism and poverty, improving pain management, and increasing access to treatment. The researchers suggested an ecological framework focused on regulatory practices for controlled substances, reform for criminal justice policies, increases in the number of treatment facilities, program development for stigma reduction, safer prescribing practices, and improved data collection to boost allocation of resources. Their chosen methodology utilized the National Vital Statistics System data ranging from 1999 to 2017. They used the International Classification of diseases to identify drug overdose deaths involving any opioid. These deaths were age-adjusted rates per 100,000 population. The researchers used joinpoint regression to identify trends in opioid-related overdose deaths among racial/ethnic groups of metropolitan and non-metropolitan residence. They classified race/ethnicity into four categories (non-Hispanic white, non-Hispanic black, Hispanic, and non-Hispanic other). Metropolitan and non-metropolitan residence was based on the six levels of the 2013 National Center for Health Statistics' urbanization classification scheme. The four metropolitan levels included large central metro (county population greater than 1 million with a principal city), large fringe metro (county population greater than 1 million without a principal city), medium-small metro (medium was defined as a population of 250,000–99,999 and small was defined as a population less than250,000). The two non-metropolitan levels included micropolitan and noncore. Lippold et al.'s findings support the need for additional studies of opioid misuse across races and geographic areas.

Sadler and Fur-Holden (2019) examined the epidemiology of opioid overdose in Flint and Genesee County, Michigan, finding opioid overdoses more prevalent in certain geographic regions. Burton et al. (2019) noted that opioid misuse and opioid-related overdose deaths have significantly increased over the past decade. According to Abbasi et al. (2019), 17,029 of the fatal overdose deaths in the United States in 2017 were attributable to prescription opioids. Addressing opioid misuse is an imperative yet complex task. Besides addiction, opioid use disorders are associated with poor outcomes on a host of socioeconomic disadvantages (Kumari et al., 2016).

Rural Disparities

POM incidence often varies according to rural/urban residence. Rigg and Nicholson (2019) approached the problem of POM among the African American rural population by conducting a rural–urban comparison of risk and prevalence. They proposed that rural status grants unique psychosocial, clinical, and demographic profiles. They used multivariate logistic regression models of data that ranged from 2012 to 2016 from the NSDUH. The sample was adjusted to include only non-Hispanic African Americans aged 18 and older residing in rural and urban areas. The outcome variable was defined as past year POM (morphine, methadone, Dilaudid, Demerol, oxycodone, hydrocodone, and codeine). Their findings revealed that rural and urban African Americans possess similar reported rates of POM. Factors correlating significantly with POM among rural residents include binge drinking, an arrest record, emergency department visits, high school graduation, or being over the age of 50 years. Rigg and Nicholson identified the need for further research specific to rural residence and POM. A more concise understanding of these profiles could guide more effective and targeted interventions.

Location proved to be essential in determining accessibility and quality of resources. Location can greatly influence opioid use disorder treatment, such as opioid agonist therapy. Wyse et al. (2019) examined predictive factors of opioid agonist treatment-seeking among individuals with opioid use disorder. They used mixed effects models for new clinical encounters of overdose use disorder ranging from 2000 to 2012 from the Veterans Aging Cohort Study and controls. A new clinical encounter of opioid use disorder was defined as an outpatient or inpatient encounter with a primary or secondary opioid dependence or abuse diagnosis code after a break in care and the absence of treatment for more than five months. The models allowed them to identify predictive factors of opioid agonist therapy initiation within 30 days of a new opioid use disorder encounter. Covariates and predictive factors of opioid agonist therapy identified within this study were age (<50, 50-64, and 65 and older), gender, race/ethnicity, HIV status, Hepatitis C viral infection, urban and rural residence (rurality was determined by the rural–urban commuting area codes guided by zip codes), alcohol related diagnosis, substance use diagnoses, multi-substance use diagnosis, psychiatric diagnoses (schizophrenia, post-traumatic stress disorder, bipolar disorder, anxiety, and depression), and a year of new opioid use disorder clinical encounter (early, middle, and later years of opioid agonist therapy availability). They found that opioid agonist therapy was less likely among rural residence patients. Rurality has been strongly associated with a lower likelihood for treatment-seeking in earlier research. This is due in large part to treatment programs primarily being located in urban areas.

Sadler and Fur-Holden (2019) sought to understand the geographic and demographic implications in regard to opioid overdose deaths. The data within the study entailed all 47 treatment sites (licensed to offer both inpatient and outpatient treatment services) and every opioid overdose death in Genesee County, Michigan within the time period ranging from 2013-2015, and socioeconomic data taken from the 2010 U.S. Census. The data obtained on the treatment sites were taken from the 2017 Michigan Department of Licensing and Regulatory Affairs Bureau of Health Systems' License Listing Report. Twenty-nine of the treatment sites provided medication assisted services. They used spatial joins in ArcGIS and kernel density analysis. They mapped out availability of treatment, opioid overdose death clusters, and neighborhood conditions in correlation with overdose deaths. Their findings suggest that specific geographic areas are more susceptible to opioid use and overdose deaths than others. They expressed the importance of the development of environmental strategy to effectively address the opioid epidemic.

Some strengths of the approaches discussed in the section above include the proposal that a comprehensive effort is necessary to guarantee treatment is distributed equitably and benefits those who are at high risk for opioid use disorder. Driving factors of variations in rural–urban POM were identified. Weaknesses of the approaches discussed in the section above include limitations among those represented within the data sources. Cross-sectional data prevents the establishment of causality. Self-reported data introduces response bias. All findings are not able to be generalized to populations or timeframes outside of these studies. NPOU, POM, and treatment-seeking among the rural population will build upon the aforementioned studies to address this public health issue.

Rationale of Variables

The purpose of this study was to identify sociodemographic factors associated with NPOU, POM, and treatment-seeking among the rural population. Although data exist to suggest that there are differences in rates of NPOU and POM based upon patient characteristics, the impact on certain populations is not well understood. Those residing in rural communities may be especially susceptible to NPOU and POM given higher rates of factors closely associated with NPOU and POM, namely, lower educational attainment, and lower income (Rigg & Monnat, 2015).

A correlation is apparent between substance use disorders and the fragmented and inefficient utilization of health care services (Gryczynski et al., 2020). Though treatment programs for opioid misuse have been shown to be effective, the potential barriers to seeking treatment for NPOU and POM among the rural population have not been well-studied however.

Review of Studies Related to Key Variables and Research Questions

Sociodemographic Factors of Interest (Race, Age, Sex, Education, Insurance Status)

Pouget et al. (2018) proposed that to fully gauge the future influence of POM intervention and effective opioid treatment programs, it was imperative to take into consideration the differences in opioid use across racial/ethnic groups. Johnson et al.

(2016) identified an association between drug abuse and gene expression in African Americans, suggesting that ancestry can be a predictor of substance use disorders among African Americans; however, this predictor did not hold for their European American counterparts.

According to Jones et al. (2019), more than 90% of African American shave reported experiencing racial discrimination. Discrimination elicits stress, which, in turn, can have a significant effect on physical health. Substance use often serves as a coping technique and navigation tool through a stressful trigger, such as racial discrimination (Jones et al., 2019). Although several studies have shown alcohol, tobacco, marijuana, and illicit drug use to be coping mechanisms for racial discrimination, opiate use has not received as much exploration within this context. The current opioid epidemic merits further research in regard to the relationship between racial discrimination and opiate use. Race plays a role in the opioid crisis. In Washington, DC, more than 80% of opioid deaths take place within Black communities (Jones et al., 2019). With regard to sociodemographic factors, race has proven to be a significant factor in urban populations, with African Americans being more likely to experience opioid addiction and having less access to treatment for opioid dependency than Caucasians (James &Jordan, 2018). This study aimed to identify if race is a significant factor among the rural population. Other sociodemographic factors namely age and, sex, as well as measures of socioeconomic status (education and insurance status) that also have been shown to be related to the aforementioned opioid-related outcomes (Rigg and Nicholson, 2019), were assessed.

Age may play a significant role in NPOU and POM. According to Kumari et al. (2016) 4.5 million American citizens 12 years of age and older self-reported the use of an opioid. The CDC (2020) suggests the prevalence of POM and opioid-related mortality has increased significantly among those age 18–44 years where unintentional injuries are the leading cause of death, more specifically unintentional overdoses/poisoning. Rigg and Nicholson's (2019) rural–urban comparison of prevalence and risk for NPOU and POM among African Americans revealed POM among those age 50+ varied by rural status.

Nicholson and Vincent (2019) conducted a study to identify gender differences in POM among African Americans. Data was obtained from the 2015 NSDUH. Their study revealed that there was no significant difference in gender reports of POM in the last year. Among African American women, low socioeconomic status resulted in an increase of probability for POM. Substance use, other prescription drug misuse, and overall poor health increased the probability for POM among African American men. They proposed that their study findings be taken into consideration when developing interventions for decreasing POM.

The literature suggests that educational attainment proves to be a significant predictor for NPOU and POM. Those residing in rural communities may be especially susceptible to NPOU and POM given higher rates of factors closely associated with NPOU and POM, namely, lower educational attainment (Rigg & Monnat, 2015). Nicholson and Vincent (2019) stated that educational attainment lowered the odds of POM among African American women.

Lanzillotta-Rangeley et al. (2020) identified Medicaid insurance as an independent predictor of prolonged postoperative opioid use. According to James and Jordan (2018), insurance status can present as a barrier to receiving substance use treatment. The lack of insurance can deter access to treatment. However, those who possess public health insurance face the possibility their insurance may not be accepted by a vast majority of substance use disorder treatment facilities. Finally, Wu et al. (2016) proposed that increasing access to insurance coverage is required to improve access to addiction treatment and cultivate a culture conducive for treatment-seeking. In 2014, 2 million American opioid use disorders involved prescription opioids (Reynoso-Vellejo & Rosen-Reynoso, 2018).

NPOU

In 2010, 52 million people reported nonmedical use of drugs at least once in their lifetime, with prescription opioids having the highest rate of use (Korneeva et al., 2018). According to Pouget et al. (2018), recent data show an increase in NPOU, indicating that NPOU in the United States is a significant public health concern. In the NSDUH, the U.S. Department of Health and Human Services (2019) defined NPOU as the use of a prescription opioid not prescribed, or one taken for the experience or feeling it may cause.

Several unique factors can influence NPOU. Wheeler et al. (2019) stated prescription drug abuse among immediate family members and high anxiety levels can increase an individual’s propensity for NPOU. Rigg and Nicholson (2019) proposed that various issues contribute to NPOU among African Americans, including demographic, clinical, psychosocial, and geographic factors. Santosa et al. (2020) attributed persistent opioid use to socioeconomic factors and high-risk prescribing practices. The increase in access to opioid prescriptions has led to a growing prevalence of POM, which is defined as use of a prescribed opioid in any way other than intended by the prescriber (NIDA, 2019).

POM

POM is a paramount public health issue. According to Kumari et al. (2016), POM poses a more than $55 billion financial burden in the United States. POM literature has historically overlooked African Americans. Rigg and Nicholson (2019) highlighted and contrasted the prevalence and indicators of POM among urban and rural African Americans. The researchers used data from the NSDUH spanning 2012–2016, subsequently conducting multivariate logistic regression models to identify the factors associated with POM among African American adults. Rigg and Nicholson found that urban and rural African Americans have comparable rates of POM. Additionally, substance use can serve as a predictor for substance misuse.

Reboussin et al. (2020) set out to identify if cannabis use could serve as a predictor for opioid misuse among urban African Americans from adolescence into young adulthood. The adoption of certain behaviors as an adolescent often carry well into adulthood. The researchers defined opioid misuse as the use of pain killers, narcotics, or heroin without a prescription by individuals between the ages of 19 to 26 years. To identify the influence of trajectories on opioid misuse in young adulthood, Reboussin et al. utilized logistic regressions while adjusting for peer, neighborhood, and individual factors. Their findings showed that the prevalence of opioid misuse was significantly higher for individuals who used cannabis than those with low or no cannabis use.

Various circumstances can lead to POM. Opioid use for postoperative pain management correlates with a higher risk of chronic opioid use (Swenson et al., 2018). Prolonged postoperative opioid use often leads to the use of a prescribed opioid beyond the way intended by the prescriber. Lanzillotta-Rangeley et al. (2020) conducted a study to identify factors associated with prolonged postoperative opioid use among opioid-naïve patients. The researchers reviewed electronic medical records of opioid-naïve orthopedic surgery adult patients who visited an academic medical center between January 1, 2012, and December 31, 2017. A multivariate logistic regression suggested factors associated with prolonged postoperative opioid, including Medicaid, Black race, alcohol abuse, and the comorbidities of chronic kidney disease, hypertension, mood disorder, and diabetes. Lanzillotta-Rangeley et al. proposed the investigation of clinical practices, education about non-opioid pain management alternatives for patients and clinicians, and more intentional postoperative follow-ups, especially among more vulnerable populations. Also recommended were perioperative screenings for patients as strategies for reducing prolonged postoperative opioid use. According to Prince (2015), addiction to prescription opioids usually serves as only one component of POM. Simultaneous issues may include crime or criminal justice system involvement, unemployment, physical or mental illness, additional substance use disorders, hospitalization, or overdose. As discussed above NPOU and POM have proven prevalent in the United States, let's take it a step further to explore the need for adequate opioid use disorder treatment.

Treatment-Seeking

Ahmedani et al. (2020) suggested systemic changes are necessary to increase opioid use disorder treatment among primary care patients. Despite proof as an effective treatment of opioid use disorder, opioid agonist therapy it is not widely utilized (Wyse et al., 2019). Although no racial group is exempt from the effects of the opioid epidemic, the greatest lack of access to treatment is among minority populations and even more pronounced in African American communities (James & Jordan, 2018). Several barriers are in place between African Americans and substance use treatment, including location and insurance status (James & Jordan, 2018). Treatment sites are often not convenient to the most frequent locations of overdose deaths (Sadler & Fur-Holden, 2019). In 2015, 44.1% of African Americans were enrolled for Medicaid in comparison to 35.3% of Whites; however, only 60% of U.S. counties have one or more treatment facilities that accepts Medicaid insurance (James & Jordan, 2018). African Americans have historically faced inequities in regard to health care access to providers, mental health services, and hospitals. According to James and Jordan (2018), only 10% of individuals in the United States with a substance use disorder are able to get the treatment they require.

Treatment-seeking among African Americans is greatly influenced by a lack of trust due to past experiences of mistreatment by the medical and health communities. The stigma of receiving treatment also plays a critical role in help-seeking among this population. Ultimately, the criminal justice system environment is the most common path for African Americans to receive substance use treatment.

Stein et al. (2018) observed disparities in medication treatment for opioid use disorders in disadvantaged communities, where individuals are at higher risk for such disorders. Wu et al. (2016) gathered data from diverse groups of individuals with opioid use disorder in an attempt to guide future treatment expansion. Their findings showed that the majority of individuals with opioid use disorder did not access appropriate treatment. Persons less likely to seek treatment were prescription opioid users, uninsured individuals, and African Americans. Wu et al. identified a need for the development of multidisciplinary interventions dedicated to increasing access to insurance coverage, with a specific focus on minorities and uninsured individuals. The researchers also noted the importance of changing attitudes toward addiction treatment to encourage treatment-seeking. Access to treatment varies along racial/ethnic lines; reform to existing regulations governing the provisions of treatment is necessary to facilitate equitable access for all (Goedel et al., 2020).

Summary and Conclusions

Based on the gaps identified, a concise understanding is needed regarding the sociodemographic factors (race, age, sex, education, and insurance status) that contribute to NPOU, POM, and treatment-seeking among rural populations. Despite extensive study of prescription opioid use in urban regions, the impact on rural residents is not well understood. This research is a necessary addition to the current literature to develop effective prevention measures for misuse, overdose deaths, and increase access to treatment. POM is often accompanied by other poor lifestyle behaviors and severe consequences, with the potential outcomes of addiction, criminal activity, job insecurity, misuse of other substances, mental illness, and overdose deaths (Prince, 2015). According to James and Jordan (2018), a rural location serves as a barrier to substance use treatment due to a lack of resources. The subsequent chapter focuses primarily on the research design and rationale, methodology, and threats to validity.

Chapter 3: Research Method

The purpose of this study was to determine the association between NPOU, POM, and treatment-seeking among the rural U.S. population, controlling for race, sex, age, education, and insurance status. It is necessary to develop policies that ensure equitable practices in preventing misuse and increasing access to treatment directly related to the opioid epidemic in rural U.S. communities. This chapter presents the research design and rationale, methodology, and threats to validity. The research design and rationale will show the study variables and the research design's relation to the research questions. Included in the methodology discussion are the target population, the sampling strategy, and the data analysis plan. Next will be a description of the threats to external and internal validity. The chapter concludes with ethical considerations for this research.

Research Design and Rationale

I conducted a cross-sectional quantitative study utilizing secondary data from an existing data set. I evaluated the relationship between sociodemographic factors, including race, age, sex, education, and insurance status, with NPOU, POM, and treatment-seeking for opioid misuse among individuals in rural communities. The data came from the SAMHDA 2019 NSDUH, which includes NPOU and POM data from a random sample of the U.S. population. Quantitative research allows for objectivity, providing descriptive summaries of data that promote generalizability and replication (Labaree, 2009). Surveys are cost- and time-efficient, a practical approach for data collection from any sample size and multiple sources (Gaille, 2020). Surveys allow for the comparison of results and analysis of data.

Methodology

This section focuses on how I conducted the study by defining the target population, identifying the sampling procedure, managing and analyzing secondary data, and identifying instrumentation, operationalization of constructs, threats to validity, and ethical considerations.

Population

The target population for this study was rural U.S. residents ages 12 years and older who took part in SAMHDA/NSDUH surveys in 2019. The survey had 67,507 respondents, 19.6% of whom identified as rural residents. Thus, the sample for this study was 13,231.

Sampling and Sampling Procedures

I used the secondary data source of NSDUH 2019 survey data (SAMHDA, 2019) for this study. Criteria for the 67,507 respondents were based on noninstitutionalized residence and an age of 12 years or older. This is a stratified example representative of civilian members of the noninstitutionalized population in the United States (SAMHDA, 2019). The 2019 NSDUH incorporated data from 50 states and the District of Columbia using an independent, multistage area probability sample. Survey administration was via computer-assisted personal interviews and audio self-interviews.

The survey has undergone several sample redesigns over the years (SAMHDA, 2019). The current design provides a cost-effective sample allocated to the largest states, sustaining adequate sample sizes within the smaller states and supporting small-area probability at both the substate and state levels. The 2019 survey sample involved a 50-

state design with an independent, multistage area probability sample for each state and the District of Columbia (SAMHDA, 2019). To increase accuracy when estimating drug use among the older population, the 2019 survey incorporated extra samples from individuals 26 years or older. Table 1 presents the demographic percentages of the survey respondents.

Table 1

Demographic Percentages of Survey Respondents

Variable	Percentage (%)
Race	
1 = Non-Hispanic White	57.2
2 = Non-Hispanic Black or African American	12.9
3 = Hispanic or Latino	19.3
4 = Other	10.6
Age	
1 = 12–17 years	25.0
2 = 18–years	25.0
3 = 26–34 years	15.0
4 = 35 or older	35.0
Sex	
1 = Male	53.1
2 = Female	46.9
Residence	
Rural	19.6
Urban	80.4

Sampling Frame

The sampling frame for this study is self-identified rural residents (a) surveyed in NSDUH 2019, (b) ages 12 and older, (c) having primary or secondary U.S. household residence, and (d) of all reported races and ethnicities. The sampled population included rural residents who have used nonmedical prescription opioids, misused prescription opioids, or sought treatment versus those who have not used opioids as well as those who used them appropriately to determine the associations between NPOU, POM, treatment-seeking, and sociodemographic factors (i.e., race, sex, age, education, and insurance status). Data from the cross-sectional 2019 NSDUH came from a single survey of participants, with no follow-up. The use of this data set constituted secondary data analysis, allowing me to observe factors from a specific period of reported cases of NPOU and POM.

Since 2014, the NSDUH has implemented a cost-effective sample allocation to the largest states while ensuring substantial representation in the smaller states (SAMHDA, 2019). This method allows for small area estimation at the state and substate levels. In this study, I used the sample restricted to the rural population.

Inclusion and Exclusion Criteria

This study was an analysis of NSDUH survey data from respondents aged 12 years and older. The inclusion criteria were rural residence respondents within this age group; excluded were data from urban and metropolitan populations.

Justification for the Effect Size, Alpha Level, and Power Level

I selected the minimum effect size to ensure the greatest external validity for this multistage, probability sampling study. I used the traditional alpha level of .05 to reduce the likelihood of Type 1 errors. The alpha level is the probability of rejecting the null hypothesis when it proves to be true (Essoe, 2015). G*Power (Demidenko, 2007) is a means to estimate a priori (see Table 2) and post hoc statistical power. With a predetermined sample size (13,231) to use for statistical analyses, I needed to be able to identify how much power this sample size could provide to detect significant differences. At 80% power, the detectable odds ratio would have been as small as 1.49 using logistic regression; thus, the total sample size needed was936.

The input included a two-tailed test, with $Pr\ (Y = 1|\ X = 1)\ H_0$ identifying the probability that sociodemographic factors (i.e., race, age, sex, education, and insurance status) are not associated with NPOU, POM, and treatment-seeking among rural Americans. With a multiple correlation coefficient of 0.4, the R-squared value was defined and set at 0.16 because there was no information presented to make an assumption of a different value. R-squared represents the amount of variability in the main predictor accounted for by the covariates. The X distribution was set as binomial for the binomial predictor. The X parm π represents the proportion of cases of nonmedical prescription opioid users, prescription opioid misusers, and treatment seekers. I expected that the number of users, misusers, treatment seekers, and nonusers, nonmisusers, and nontreatment seekers would be balanced, thus justifying a value set at 0.5.

The output in Table 2 shows a critical *z* value of 1.95. Researchers use the critical *z* value when the sampling distribution is normal. A total sample size of 936 and an actual power of 0.80 were components of the output of this statistical power calculation.

Table 2

*Logistic Regression a Priori Statistical Power Calculation Using G*Power*

z tests - Logistic regression		
Options:	Large sample z-Test, Demidenko (2007) with var corr	
Analysis:	Compromise: Compute implied α & power	
Input:	Tail(s)	= Two
	Odds ratio	= 1.49
	Pr(Y=1|X=1) H0	= 0.45
	α err prob	= 0.05
	Power (1-β err prob)	= 0.80
	R^2 other X	= 0.16
	X distribution	= Binomial
	X parm π	= 0.5
Output:	Critical z	= 1.9599640
	Total sample size	= 936
	Actual power	= 0.8003655

Data Accessibility and Permissions

The 2019 NSDUH data set is available in the public domain; thus, the use of the data set does not require SAMHDA's permission. SAMHDA (2019) protected respondent anonymity by removing identifying information from survey responses. This study was for observational and evaluation purposes only. I requested a Walden University Institutional Review Board (IRB) limited review and approval before accessing and using the data (IRB approval number: 05-12-21-0623494).

Data Collection and Management

For this study, I used NSDUH 2019 data collected by SAMHDA for secondary data analysis. The NSDUH serves as a critical data source for illicit drug use, alcohol consumption, and tobacco use and the mental health status of U.S. residents (SAMHDA, 2019). SAMHDA/NSDUH 2019 is made up of public-use data files within the public domain.

Instrumentation and Operationalization of Constructs

Professionals and researchers have used NSDUH data to inform treatment and prevention programs, identify trends among substance use disorders, evaluate treatment needs, and influence health policy (NSDUH, 2019). In this study, I conducted a quantitative analysis utilizing secondary data from the NSDUH 2019 to identify factors that contribute to NPOU, POM, and treatment-seeking among the rural population. The outcomes of interest were NPOU, POM, and treatment-seeking among the surveyed rural residents. NSDUH reliability results are not available for substance use treatment due to changes to questions in the 2015–2019 surveys for prescription drugs (SAMHDA, 2019). NSDUH respondents are American household residents age 12 and over. Incomplete or missing survey data affect the external validity of the findings. Self-reporting by the respondents can result in nonresponse and recall biases. SAMHDA sought to mitigate incomplete or missing data in the 2019 NSDUH with statistical imputation and logical editing. Statistical imputation replaces missing values with appropriate response codes. Logical editing takes data from another point of the respondent’s submission to replace missing values. Nonresponse bias can also take place when a respondent chooses not to respond. The NSDUH 2019 utilizes an audio computer-assisted self-interview (ACASI) instrument. To incentivize response rates, SAMHDA offers respondents $30 to complete the NSDUH.

Operationalization

Table 3 presents the variables used in this analysis: race, age, sex, education, and insurance status. In this analysis, the dependent variables—NPOU, POM, and treatment-seeking—had two levels (*yes past 12 months* and *no past 12 months*). The independent variables included race (predictor variable of primary interest), along with age, sex, education, and insurance status (potential confounders). These variables were either nominal or ordinal.

Table 3

Measurement Level and Operational Definition of Variables

Variable	Measurement level	Definition	Assigned numerical value
Race (independent variable; predictor variable of primary interest)	Nominal	Reported race	1 = Non-Hispanic White 2 = Non-Hispanic Black or African America 3 = Hispanic or Latino 4 = Other
Age (independent variable; potential confounder)	Ordinal	Years of life at time of survey	1 = 12–17 years 2 = 18–years 3 = 26–34 years 4 = 35 or older
Sex (independent variable; potential confounder)	Nominal	Sex at birth	1 = Male 2 = Female
Education (independent variable; potential confounder)	Nominal		1 = < High school 2 = High school graduate 3 = Some college or associate degree 4 = College graduate
Insurance status (independent variable; potential confounder)	Nominal		1 = Yes 2 = No
NPOU (dependent variable)	Nominal	Use w/o own Rx in past 12 months	1 = Yes 2 = No
POM (dependent variable)	Nominal	Use not directed by doctor in past 12 months	1 = Yes 2 = No
Treatment-seeking (dependent variable)	Nominal	Received drug treatment in past 12 months	1 = Yes 2 = No

Data Analysis Plan

I performed multiple logistic regression analyses to identify relationships, measure levels of significance of associations between independent and dependent variables, and reduce statistical errors. I calculated an odds ratio to measure the strength of an association between two variables (Real Statistics, 2020). An odds ratio of exactly 1 indicates that the variables are independent of one another. When the odds ratio is more than 1, there is a higher association between the variables; in comparison, an odds ratio of less than 1 means that one variable reduces the odds of the presence of the other. Table 4 presents a summary of the statistical procedures and the relevant questions and hypotheses.

Prior to running the logistic regression models, I examined the pairwise relationships between the independent variables: race, age, sex, education, and insurance status to assess potential multicollinearity. Multicollinearity refers to high intercorrelations among independent variables, the statistical inferences made in the presence of multicollinearity may prove to be unreliable (Statistics Solutions, 2021). These relationships were assessed using the Phi coefficient. The relationships did not appear to be highly correlated. I did not exclude any of the variables from the models. Note that as race is the primary predictor of interest, it was included in every model. I assessed the fit of the final models for each research question with the Hosmer–Lemeshow goodness of fit statistic (Real Statistics, 2020). I saw no evidence of lack of fit. Multivariable logistic regression analyses enabled the estimation of how the odds of NPOU, POM, and treatment-seeking for the associations between these outcome variables and predictor variable vary with each potential confounding variable collected in the 2019 NSDUH.

The 2019 NSDUH employs a unique sampling procedure and survey design, which requires an approach of weighted analysis, as thoroughly described in the codebook. A weighted analysis allowed me to more accurately estimate standard errors and parameters. The associations between the predictor variables and outcome variables were adjusted for the different covariates: race, sex, age, education, and insurance status. Statistical Package for the Social Sciences (IBM SPSS; Version 25) software was utilized for the data analysis in this study.

Table 4

Research Questions, Hypotheses, and Appropriate Statistical Procedures

Research question	Hypothesis	Variables	Statistical procedure
1. What sociodemographic factors (race, age, sex, education, and insurance status) are independently associated with NPOU among rural Americans after adjusting for the other sociodemographic factors?	H_0: The given sociodemographic factor is not independently associated with NPOU among rural Americans. H_a: The given sociodemographic factor is independently associated with NPOU among rural Americans.	DV: NPOU IV: race, age, sex, education, and insurance status	Multiple logistic regression
2. What sociodemographic factors (race, age, sex, education, and insurance status) are independently associated with POM among rural Americans after adjusting for the other sociodemographic factors?	H_0: The given sociodemographic factor is not independently associated with POM among rural Americans. H_a: The given sociodemographic factor is independently associated with POM among rural Americans.	DV: POM IV: race, age, sex, education, and insurance status	Multiple logistic regression
3. Among rural Americans who have misused prescription opioids, what sociodemographic factors (race, age, sex, education, and insurance status) are independently associated with seeking treatment after adjusting for the other sociodemographic factors?	H_0: Among rural Americans who have misused prescription opioids, the sociodemographic factor is not independently associated with seeking treatment. H_a: Among rural Americans who have misused prescription opioids, the sociodemographic factor is independently associated with seeking treatment.	DV: treatment-seeking IV: age, sex, education, and insurance status	Multiple logistic regression

Note. DV = dependent variable; IV = independent variable; NPOU = nonmedical prescription opioid use; POM = prescription opioid misuse.

Threats to Validity

Validity refers to the extent to which a study accurately represents or evaluates the specific concept that the researcher is attempting to measure (Everitt & Skrondal, 2010).

External Validity

According to Statistics Solutions (2022), external validity refers to the extent to which study findings can be generalized to a larger group of the population about whom the researcher seeks to make inferences. Without external validity, the application of the study findings cannot take place outside of the study. The 2019 NSDUH included data from 50 states and the District of Columbia using an independent, multistage area probability sample. The selected sample was meant to be representative of the U.S. population ages 12 and older (SAMHDA, 2019). It is necessary to weight the data to provide unbiased estimations for survey findings in the population represented by the 2019 NSDUH.

Although the 2019 NSDUH was successful in collecting invaluable information on various drug-related and health topics, it has limitations. The first limitation is incomplete or missing data, which affects the external validity of the findings. SAMHDA (2019) mitigated incomplete or missing data through the use of statistical imputation and logical editing. Statistical imputation replaces missing values with appropriate response codes; logical editing takes data from another point in the respondent's submission to replace missing values. The second limitation is that respondent self-report can result in nonresponse and recall biases. Nonresponse bias can also occur when a respondent chooses not to respond. To incentivize response rates, SAMHDA offered individuals $30 to complete the NSDUH, which led to improved response rates (SAMHDA, 2019). The 2019 NSDUH had an overall response rate of 45.8% for ages 12 and older.

Internal Validity

Internal validity is when a study's findings are due to manipulation of the independent variable and are not influenced by an outside factor (Statistics Solutions2022). The utilized secondary data from the 2019 NSDUH on the rural population ages 12 and older. One challenge that presented early in the developmental stages was selecting an appropriate data set representative of the desired variables. An additional challenge was the appropriate evaluation of the chosen variables. The reliability of self-reported data could be affected by participant nonresponse. The survey authors attempted to mitigate nonresponse by offering an incentive to complete the survey. The survey also includes questions that cover sensitive topics. To ensure respondent anonymity and confidentiality, the NSDUH survey did not collect any personal information.

Construct Validity

Construct validity refers to whether the instrument is able to successfully measure the intended concept (Pam, 2013). SAMHDA developed the survey utilizing a standardized tool. The NSDUH has taken several steps over the years to ensure quality and efficiency in the data collection process as well as the overall validity of the study. In 1999, SAMHDA (2019) transferred the survey from a paper questionnaire to its current computer-assisted administration. The most relevant steps entailed 2015 revisions to the prescription drug/pain relievers questions. Formerly focused strictly on lifetime use and misuse, the questions now center around use and misuse over the past 12 months. The revised survey included two measures in regard to substance use treatment in the past 12 months, now gauging the need for and receipt of treatment. The NSDUH also compiles data on where treatment is received and the barriers associated with treatment-seeking. In 2001, the survey authors modified data collection quality control procedures.

Ethical Procedures

This study was conducted after obtaining permission from and adherence to the ethical standards specified by the Walden University IRB. This study was also conducted based on SAMHDA's ethical principles as applied in the survey administration and data collection. SAMHDA obtained respondents' informed consent prior to their participation in the survey. Informed consent ensures that respondents are fully aware of their participation within a research study and that no coercion or deception takes place. The 2019 SAMHDA/NSDUH is available in a public domain for secondary data analysis; therefore, it was not necessary to obtain permission to access the data.

Summary

In Chapter 3, I presented the methodology for the 2019 NSDUH secondary data collected by SAMHDA. This entailed the inclusion of the proposed research design and rationale, the research population, sampling procedures, and data collection. I also presented the instruments to be utilized within this proposed study, the data analysis plan, potential threats to validity, and ethical procedures. Chapter 4 includes the results and findings of the study relative to the research questions.

Chapter 4: Results

The purpose of this quantitative study was to use NSDUH 2019 cross-sectional data set collected by the SAMHDA for secondary data analysis to determine if associations exist between sociodemographic factors (race, age, sex, education, and insurance status) and NPOU, POM, and treatment-seeking among rural Americans age 12 years and older. As noted in earlier chapters, NSDUH defined NPOU as individuals having used a pain reliever without their own prescription in the past 12 months, POM as having used a pain reliever in a way other than directed in the past 12 months, and treatment-seeking as having reported receiving alcohol or drug treatment in the past 12 months. Chapter 4 includes the results of statistical analysis on data collected from NSDUH. I describe the time frame and sample demographics, the representativeness of the sample, and the univariate characteristics and analysis of the sample. In addition, the chapter presents the results of the logistic regression models for RQ1, RQ2, and RQ3, as provided below. The following research questions and hypotheses guided this study:

RQ1: What sociodemographic factors (race, age, sex, education, and insurance status) are independently associated with NPOU among rural Americans after adjusting for the other sociodemographic factors?

For each sociodemographic factor, the null and alternative hypotheses were:

$H_0$1: The given sociodemographic factor is not independently associated with NPOU among rural Americans.

H_a1: The given sociodemographic factor is independently associated with NPOU among rural Americans.

RQ2: What sociodemographic factors (race, age, sex, education, and insurance status) are independently associated with POM among rural Americans after adjusting for the other sociodemographic factors?

For each sociodemographic factor, the null and alternative hypotheses were:

$H_0$2: The given sociodemographic factor is not independently associated with POM among rural Americans.

H_a2: The given sociodemographic factor is independently associated with prescription

opioid misuse among rural Americans.

RQ3: Among rural Americans who have misused prescription opioids, what sociodemographic factors (race, age, sex, education, and insurance status) are independently associated with seeking treatment after adjusting for the other sociodemographic factors?

For each sociodemographic factor, the null and alternative hypotheses were:

$H_0$3: Among rural Americans who have misused prescription opioids, the sociodemographic factor is not independently associated with seeking treatment.

*H*a3: Among rural Americans who have misused prescription opioids, the sociodemographic factor is independently associated with seeking treatment.

Data Collection

The NSDUH is a critical data source for information on illicit drug use, alcohol consumption, and tobacco use and the mental health status of U.S. residents (SAMHDA, 2019). The NSDUH is an annual survey involving a screening phase followed by an interview phase, resulting in estimates at the national, state, and substate levels. Each year, approximately 67,000 individuals aged 12 and older engage in audio, computer-assisted self-interviews or one-on-one interviews in their households. The 2019 NSDUH data analyzed in this study comprised public-use data files in the public domain from the SAMHDA website. I utilized 2019 data that pertained to sociodemographic factors (race, age, sex, education, and insurance status), NPOU, POM, and treatment-seeking among rural Americans to conduct multiple logistic regression analyses, as identified by the research questions guiding this study. In May 2021, I downloaded in an SPSS file format the raw data set comprising 56,136 cases. I removed cases from metropolitan areas, leaving a final sample of 11,020 cases available for analysis, with the remaining missing responses handled using listwise deletion.

Time Frame and Response Rates

NSDUH 2019 data collection occurred from January 1 to December 31, 2019. To increase response rates, NSDUH 2019 provided each respondent a $30 incentive. This enticement resulted in a weighted household screening response rate of 70.50% and a weighted interview response rate of 64.92% for individuals 12 and older (SAMHDA, 2019).

Baseline Descriptive and Demographics of the Sample

As noted, the sample population was 11,020 rural Americans aged 12 years and older. Cases responded to questions regarding NPOU, POM, and treatment-seeking. Discussed in the following section and presented in Table 5 are descriptive statistics for the research variables.

Representativeness of the Sample

The SAMHDA provides substance abuse and mental health research data for public use for the assessment of substance abuse and mental health problems (SAMHDA, 2019). SAMHDA (2019) selected the sample for the 2019 NSDUH utilizing a multistage, stratified sample design. The full, restricted-use analytic data file incorporates one record per each respondent selected from Stage 5 (67,625 individuals). Using a statistical disclosure limitation method was the means to preserve the respondents' confidentiality. The sample was representative of the U.S. population overall and each of the 50 states and the District of Columbia individually, allowing for estimates at the national, regional, state, and substate levels.

Univariate Characteristics of the Sample

Table 5 shows the univariate characteristics and descriptive statistics for the research variables. The majority of the participants in the sample identified their race as White (n = 8,320, 75.5%). Slightly over one third of the participants were 35 years of age or older (n = 4,060, 36.8%). Most of the participants were women (n = 5,811, 52.7%). With regard to education, 24.7% of participants (n = 2,723) had a high school degree, and 26.6% (n = 4,998) had at least some college. The majority of participants had health insurance (n = 9,908, 89.9%). Approximately 2.0% (n = 221) indicated having used pain relievers without their own prescription in the past 12 months (i.e., NPOU), and less than 1% (n = 90) had used pain relievers in a way other than directed in the past 12 months (i.e., POM). Only 1.8% of participants (n = 203) reported receiving alcohol or drug treatment in the past 12 months (i.e., treatment-seeking).

Table 5

Univariate Characteristics (Descriptive Statistics) of the Sample

Variable	Frequency	%
Race		
White	8,320	75.5
Black	800	7.3
Hispanic	964	8.7
Other	936	8.5
Age (years)		
12–17	2,682	24.3
18–25	2,722	24.7
26–34	1,556	14.1
35 and older	4,060	36.8
Sex		
Male	5,209	47.3
Female	5,811	52.7
Education		
Less than high school	1,096	9.9
High school	2,723	24.7
Some college	2,061	18.7
Associate degree	876	7.9
College graduate	1,582	14.4
Health insurance coverage		
Covered	9,908	89.9
Not covered	1,112	10.1
Nonmedical prescription opioid use (NPOU)		
No	10,730	97.4
Yes	221	2.0
Missing	69	0.6
Prescription opioid misuse (POM)		
No	10,862	98.6
Yes	90	0.8
Missing	68	0.6
Treatment-seeking		
No	10,648	96.6
Yes	203	1.8
Missing	169	1.5

Study Results

The purpose of conducting this research was to examine whether associations exist between sociodemographic factors (race, age, sex, education, and insurance status) and NPOU, POM, and treatment-seeking among rural Americans aged 12 years and older. The objective was to justify the need for new and improved policy-driven objectives to ensure equitable practices for this vulnerable population by preventing opioid misuse and increase access to treatment. Several hypotheses developed and answered in research questions were the means to determine if there were relationships between sociodemographic factors (race, age, sex, education, and insurance status) and NPOU, POM, and treatment-seeking. In contrast, the null hypotheses were the means to determine if there were no relationships between sociodemographic factors (race, age, sex, education, and insurance status) and NPOU, POM, and treatment-seeking.

Regression Diagnostics for RQ1

RQ1: What sociodemographic factors (race, age, sex, education, and insurance status) are independently associated with NPOU among rural Americans after adjusting for the other sociodemographic factors?

Addressing RQ1 entailed conducting a logistic regression analysis. The dependent variable was NPOU, coded as 0 = *no* and 1 = *yes*. The predictor variables were race, age, sex, education, and health insurance coverage. Calculating variance inflation factors (VIFs) was to examine multicollinearity among the predictor variables. In a regression model, the VIF shows the impact of collinearity among the variables, with a value greater than 10 indicating multicollinearity (Research Consultation, 2007). One can also assess multicollinearity by examining the correlations between predictors to identify a high level of association. All VIF values were below 10 (see Table 6), and bivariate correlations between predictors were low (see Table 7), indicating no severe multicollinearity in the data. The Hosmer–Lemeshow test was a statistic used to determine the model goodness of fit; the results were not significant, $\chi^2(7) = 6.12$, $p = .526$, indicating that the observed data did not significantly differ from the predicted model—in other words, there was no evidence of lack of model fit.

Table 6

Variance Inflation Factors

Variable	Variance inflation factors
Race	
White	2.45
Black	1.73
Hispanic	1.87
Age	
12–17	2.26
18–25	1.30
26–34	1.19
Sex	
Male	1.01
Education	
Less than high school	1.60
High school	2.14
Some college or associate degree	2.15
Health insurance coverage	
Covered by health insurance	1.05

Table 7

Bivariate Correlations for Predictors of Nonprescription Opioid Misuse

Variable	1	2	3	4	5	6	7	8	9	10	11
NPOU	–										
Ethnicity											
White	.00	–									
Black	-.02	-.49**	–								
Hispanic	-.01	-.54**	-.09**	–							
Age											
12–17	-.05**	-.07**	-.01	.07**	–						
18–25	.04**	-.07**	.04**	.04**	-.32**	–					
26–34	.02*	.01	.00	.01	-.23**	-.23**	–				
Sex											
Male	.02	.00	-.03**	.00	.04**	.00	-.02	–			
Education											
Less than high school	.04**	-.06**	.03**	.05**	-.19**	.12**	.01	.03**	–		
High school	.02*	-.02*	.04**	-.01	-.32**	.16**	.06**	.04**	-.19**	–	
Some college or associate degree	.01	.04**	.00	-.04**	-.34**	.15**	.07**	-.08**	-.20**	-.35**	–
Health insurance coverage											
Covered by health insurance	-.03**	.07**	-.03**	-.10**	.11**	-.08**	-.06**	-.05**	-.12**	-.08**	.00

**p*< .05. ***p*< .01.

Table 8 shows the results of the logistic regression model predicting NPOU. Race was a significant predictor of NPOU, with Black participants 0.25 times the odds of all other races to have used pain relievers without their own prescription in the past 12 months (*OR*= 0.25, 95% CI = 0.09–0.67, *p* = .006). Age was a significant predictor of NPOU. There were greater odds for participants in the 18 to 25 (*OR*= 2.11, 95% CIs 1.37–3.26, *p* = .001) and 26 to 34 (*OR*= 2.79, 95% CI = 1.75–4.45, *p*< .001) age groups to have used pain relievers without their own prescription in the past 12 months than persons aged 12 to 17 and 35 and older. Education was another significant predictor of NPOU, with greater odds for participants who had completed less than high school (*OR* = 2.29, 95% CI = 1.03–5.10, *p*=.043), high school (*OR*= 2.15, 95% CI = 1.06–4.33, *p* =

.033), or some college (*OR* = 2.16, 95% CI =1.07–4.32, *p* = .031) than those who completed an associate degree or college graduates to have used pain relievers without their own prescription in the past 12 months. Insurance coverage was a significant predictor of NPOU, with participants covered by health insurance having 0.34 times the odds as those without coverage to have used pain relievers without their own prescription in the past 12 months (*OR* = 0.34, 95% CI = 0.21–0.55, *p*< .001). Sex, however, was not a significant predictor of NPOU. The null hypotheses corresponding to race, age, education, and insurance status were rejected. I failed to reject the null hypothesis corresponding to sex.

Table 8

Binary Logistic Regression Predicting Nonprescription Opioid Use

						95% CI *OR*	
Variable	*B*	*SE*	*t*	Sig.	*OR*	Lower	Upper
Race							
White	-0.28	0.33	-0.86	.388	0.75	0.40	1.43
Black	-1.40	0.50	-2.77	.006	0.25	0.09	0.67
Hispanic	-0.77	0.48	-1.60	.110	0.46	0.18	1.19
Age							
12–17	0.05	0.45	0.12	.905	1.06	0.44	2.55
18–25	0.75	0.22	3.37	.001	2.11	1.37	3.26
26–34	1.03	0.24	4.31	< .001	2.79	1.75	4.45
Sex							
Male	0.32	0.20	1.59	.111	1.38	0.93	2.04
Education							
Less than high school	0.83	0.41	2.02	.043	2.29	1.03	5.10
High school	0.76	0.36	2.13	.033	2.15	1.06	4.33
Some college or associate degree	0.77	0.36	2.16	.031	2.16	1.07	4.32
Health insurance coverage							
Covered by health insurance	-1.07	0.24	-4.43	< .001	0.34	0.21	0.55

Regression Diagnostics for RQ2

RQ2: What sociodemographic factors (race, age, sex, education, and insurance status) are independently associated with POM among rural Americans after adjusting for the other sociodemographic factors?

A second logistic regression model was fit to address RQ2. The dependent variable in this analysis was POM, coded as 0 = *no* and 1 = *yes*. The predictor variables were race, age, sex, education, and health insurance coverage. Calculating VIFs was a means to examine multicollinearity among the predictor variables. All VIF values were below 10 (see Table 6), and bivariate correlations between predictors were low (see Table 9), indicating no severe multicollinearity in the data. The Hosmer–Lemeshow test was appropriate to determine the goodness of fit for the model; the results were not significant, $\chi^2(8) = 12.75$, $p = .121$, indicating that the observed data did not significantly differ from the predicted model.

Table 9

Bivariate Correlations for Predictors of Prescription Opioid Misuse

Variable	1	2	3	4	5	6	7	8	9	10	11
POM	–										
Ethnicity											
White	.01	–									
Black	-.01	-.49**	–								
Hispanic	-.01	-.54**	-.09**	–							
Age											
12–17	-.01	-.07**	-.01	.07**	–						
18–25	.03**	-.07**	.04**	.04**	-.32**	–					
26–34	.02	.01	-.01	.01	-.23**	-.23**	–				
Sex											
Male	.01	.00	-.03**	.00	.04**	.00	-.02	–			
Education											
Less than high school	.01	-.06**	.03**	.05**	-.19**	.12**	.01	.03**	–		
High school	.01	-.02*	.04**	-.01	-.32**	.16**	.06**	.04**	-.19**	–	
Some college or associate degree	.00	.04**	.00	-.04**	-.34**	.15**	.07**	-.08**	-.20**	-.35**	–
Health insurance coverage											
Covered by health insurance	-.01	.07**	-.03**	-.10**	.11**	-.08**	-.06**	-.05**	-.12**	-.08**	-.01

**p*< .05. ***p*< .01.

Table 10 presents the results of the logistic regression model predicting POM. Race was a significant predictor of POM, with Black participants 0.08 times the odds of all other races to have used pain relievers in a way other than directed in the past 12 months (*OR* = 0.08, 95% CI = 0.01–0.46, *p* = .005). Age was a significant predictor of POM, such that participants in the 12 to 17 age group had greater odds than those aged 18 and above to have used pain relievers in a way other than directed in the past 12 months (*OR* = 3.41, 95% CI = 1.16–10.03, *p* = .026). Sex, education, and insurance coverage were not significant predictors of POM. The null hypotheses corresponding to race and age were rejected. I failed to reject the null hypotheses corresponding to sex, education, and insurance coverage.

Table 10

Binary Logistic Regression Predicting Prescription Opioid Misuse

Variable	*B*	*SE*	*t*	Sig.	*OR*	95% CI *OR* Lower	95% CI *OR* Upper
Race							
White	-0.45	0.75	-0.60	.551	0.64	0.15	2.79
Black	-2.58	0.92	-2.80	.005	0.08	0.01	0.46
Hispanic	-1.33	1.10	-1.21	.227	0.27	0.03	2.29
Age							
12–17	1.23	0.55	2.22	.026	3.41	1.16	10.03
18–25	0.71	0.51	1.40	.162	2.04	0.75	5.55
26–34	0.90	0.52	1.73	.083	2.46	0.89	6.83
Sex							
Male	0.69	0.37	1.87	.061	2.00	0.97	4.11
Education							
Less than high school	1.57	0.89	1.77	.077	4.79	0.84	27.22
High school	0.68	0.55	1.25	.212	1.97	0.68	5.74
Some college or associate degree	0.78	0.53	1.47	.141	2.17	0.77	6.10
Health insurance coverage							
Covered by health insurance	-0.73	0.57	-1.29	.199	0.48	0.16	1.47

Regression Diagnostics for RQ3

RQ3: Among rural Americans who have misused prescription opioids, what sociodemographic factors (race, age, sex, education, and insurance status) are independently associated with seeking treatment after adjusting for the other sociodemographic factors?

A third logistic regression model was fit to address RQ3. The dependent variable in this analysis was treatment-seeking behavior, coded as 0 = *no* and 1 = *yes*. The predictor variables were race, age, sex, education, and health insurance coverage. VIFs were the calculation performed to examine multicollinearity among the predictor variables. All VIF values were below 10 (see Table 6), and bivariate correlations between predictors were low (see Table 11), indicating no severe multicollinearity in the data. The Hosmer–Lemeshow test allowed me to determine the model goodness of fit; the results were not significant, $\chi^2(8) = 1.74$, $p = .988$, indicating that the observed data did not significantly differ from the predicted model.

Table 11

Bivariate Correlations for Predictors of Treatment-Seeking

Variable	1	2	3	4	5	6	7	8	9	10	11
Treatment-seeking	–										
Ethnicity											
White	.01	–									
Black	-.01	-.49**	–								
Hispanic	.00	-.54**	-.09**	–							
Age											
12–17	-.04**	-.07**	-.01	.07**	–						
18–25	.01	-.07**	.05**	.04**	-.32**	–					
26–34	.04**	.01	-.01	.01	-.23**	-.24**	–				
Sex											
Male	.02*	.00	-.03*	.00	.05**	.00	-.02	–			
Education											
Less than high school	.05**	-.07**	.03**	.04**	-.19**	.12**	.01	.03**	–		
High school	.02*	-.02*	.04**	-.01	-.32**	.16**	.06**	.04**	-.19**	–	
Some college or associate degree	.01	.04**	-.01	-.04**	-.34**	.14**	.06**	-.08**	-.20**	-.35**	–
Health insurance coverage											
Covered by health insurance	-.03**	.07**	-.03**	-.10**	.11**	-.08**	-.05**	-.05**	-.12**	-.08**	-.01

$^{*}p < .05$. $^{**}p < .01$.

Table 12 shows the results of the logistic regression model predicting treatment-seeking. Age was a significant predictor of treatment-seeking, as participants in the 26 to 34 age group had greater odds than those ages 12 to 25 and 35 and up to have received alcohol or drug treatment in the past 12 months (*OR* = 1.88, 95% CI = 1.05–3.38, $p = .035$). Sex was a significant predictor of treatment-seeking, with men 1.93 times the odds as women to have received alcohol or drug treatment in the past 12 months (*OR* =

1.93, 95% CI = 1.23–3.03, *p* = .004). Education was a significant predictor of treatment-seeking such that participants who had completed less than high school (*OR* = 8.41, 95% CI = 3.65–19.34, *p*< .001), high school (*OR* = 3.47, 95% CI = 1.54–7.82, *p* = .003), or some college (*OR* = 3.89, 95% CI = 1.78–8.51, *p* = .001) had greater odds than those with an associate degree and college graduates to have received alcohol or drug treatment in the past 12 months. Race and insurance coverage were not significant predictors of treatment-seeking. The null hypotheses corresponding to age, sex, and education were rejected. I failed to reject the null hypotheses corresponding to race and insurance coverage.

Table 12

Binary Logistic Regression Predicting Treatment-Seeking

						95% CI *OR*	
Variable	*B*	*SE*	*t*	Sig.	*OR*	Lower	Upper
Race							
White	-0.13	0.61	-0.21	.836	0.88	0.27	2.91
Black	-0.08	0.79	-0.10	.919	0.92	0.20	4.34
Hispanic	-0.33	0.77	-0.42	.672	0.72	0.16	3.26
Age							
12–17	0.69	0.46	1.52	.130	2.00	0.82	4.90
18–25	0.03	0.28	0.10	.917	1.03	0.60	1.77
26–34	0.63	0.30	2.11	.035	1.88	1.05	3.38
Sex							
Male	0.66	0.23	2.85	.004	1.93	1.23	3.03
Education							
Less than high school	2.13	0.43	5.01	<.001	8.41	3.65	19.34
High school	1.25	0.41	3.01	.003	3.47	1.54	7.82
Some college or associate degree	1.36	0.40	3.40	.001	3.89	1.78	8.51
Health insurance coverage							
Covered by health insurance	-0.59	0.33	-1.77	.077	0.56	0.29	1.07

Summary

Chapter 4 included the study purpose, research questions and hypotheses, data collection, time frame and response rates, descriptive demographics of the sample, representativeness of the sample, univariate characteristics of the sample, and study results and key findings. I used the NSDUH 2019 data collected by SAMHDA as secondary data to examine the associations between the independent variables of race, age, sex, education, and insurance status and the dependent variables NPOU, POM, and treatment-seeking in the past year.

In this chapter, I presented the results and findings of this study. With regard to the analysis and findings, I conducted a series of logistic regressions on NSDUH data to address the research questions. For RQ1, the results showed that race, age, less education, and insurance coverage were positively and significantly associated with NPOU. The RQ2 results showed that race and younger age were positively associated with POM. Finally, the RQ3 results showed that young adult age, male sex, and less education were significantly associated with treatment-seeking.

A detailed interpretation and analysis of the findings of this study appear in Chapter 5, as well as an overview of the research study and relevant conclusions. The chapter includes an interpretation of the findings in the context of the current literature and the theoretical framework of the SEM. Closing the chapter are recommendations and implications for positive social change and professional practice for future research.

Chapter 5: Discussion, Conclusions, and Recommendations

The purpose of this quantitative study was to determine if associations exist between sociodemographic factors (race, age, sex, education, and insurance coverage status) and NPOU, POM, and treatment-seeking among rural Americans age 12 years and older. The results showed positive associations between NPOU and Black race, younger age, less education, and health insurance coverage; Black race and younger age were positively associated with POM; and younger age, male sex, and less education were positively associated with treatment-seeking. This chapter includes an interpretation of the findings, limitations of the study, recommendations for further research, and implications for positive social change.

Interpretation of the Findings

Rural American NPOU

The results of this study provided insight into how race, age, education, and health insurance coverage are important predictors of rural Americans' NPOU. As discussed in Chapter 4, rural Black participants had greater odds of having used pain relievers without their own prescription in the past 12 months than White or Hispanic respondents.

The findings in this study contrasted with Pouget et al. (2018), Reynoso-Vallejo and Rosen-Reynoso (2018), and Korneeva et al. (2018), who found that White race was positively associated with increased rates of NPOU among the urban population compared to Black and Hispanic races. Despite a common use of nationally representative samples, the researchers also incorporated some factors outside of the scope of this study, such as urban residency, NPOU across multiple years, and polydrug use. The findings in this study aligned with Jones et al. (2019), Johnson et al. (2016), and Wheeler et al. (2019), who found the Black race was positively associated with NPOU among the urban population compared to the White race. All of these studies utilized self-reported data. Jones et al., Johnson et al., and Wheeler et al. also incorporated some factors outside the scope of this study that could not be taken into consideration, such as urban residency, racial discrimination, mental health issues, polydrug use, incarceration, and family history of NPOU.

As reported in Chapter 4, Black race was positively associated with increased NPOU. There is a lack of consensus within the literature showing White race and Black race as predictors of increased NPOU. One explanation is that the focus of the current analysis was on the rural population, and perhaps there is an interaction between race and urban/rural residency with regard to NPOU. However, this analysis was restricted to rural persons and therefore did not address urban versus rural differences.

As discussed in Chapter 4, age was also positively associated with increased NPOU, with a greater likelihood for participants ages 18 to 34 years to have used pain relievers without their own prescription in the past 12 months than persons aged 12 to 17 years and 35 years or older. According to Kumari et al. (2016), 4.5 million Americans ages 12 years and older reported using opioids. This research substantiated findings by Korneeva et al. (2018) and Santosa et al. (2020), who found the 18–25 age group positively associated with increased rates of NPOU. All three studies utilized nationally representative samples. Most individuals who reported POM described initiating prescription opioid use in their early 20s, putting them at disproportionate risk for overdose death (CDC, 2020).

As stated, less education and health insurance coverage were also positively associated with increased NPOU. There was no published literature against which to compare this study's results regarding educational attainment and health insurance coverage identified as predictors of increased NPOU among the rural population. Further research is needed to clarify the impact of education and health insurance coverage on NPOU among the rural population.

Rural American POM

The results of this study showed Black race and younger age were predictors of POM in rural Americans. The present study supported Lanzillotta-Rangeley et al. (2020) and Swenson et al.'s (2018) findings that Black race was independently associated with POM. All three studies utilized a secondary data set. As previously mentioned, the present study used data from the NSDUH. Lanzillotta-Rangeley et al. conducted a retrospective analysis of electronic medical records; in contrast, Swenson et al. used information from Optum Clinformatics that included pharmacy and medical data from a national private health insurer.

The present study also showed that younger age was positively associated with increased POM, with participants in the 12–17 age group having greater odds than those aged 18 and above to have used pain relievers in a way other than directed in the past 12 months. The findings of the present study aligned with Reboussin et al. (2020) and Nicholson and Vincent (2019), who also found that younger age was positively associated with increased POM, with the adolescent age group 14–17 years having the highest rate of POM. All three studies utilized a secondary data set; however, Reboussin et al. used a different definition of POM. One explanation for why younger age is positively associated with increased POM is that brains continue to develop into the mid-20s. Taking drugs at a young age can affect the development of the brain's prefrontal cortex, a section used in decision-making, and can lead to engaging in risky behaviors (NIH, 2016).

In another perspective, Swenson et al. (2018) found that factors independently associated with POM included increasing age. Swenson et al. incorporated some factors outside the scope of this study, such as chronic pain disorders, depression/anxiety, and substance abuse. According to the NIH (2016), there is evidence that chronic pain is more prevalent in older adults. Thus, it is logical that an increase in chronic pain among older adults could lead to an increase in POM as a coping mechanism.

Rural American Treatment-Seeking Behaviors

According to James and Jordan (2018), only 10% of individuals in the United States with a substance use disorder could access the treatment they required. As reported in Chapter 4, younger age, male sex, and persons with lower levels of education were predictors of treatment-seeking among rural Americans who have misused prescription opioids. Young adult age was positively associated with increased treatment-seeking, as participants in the 26–34 age group had greater odds of receiving drug treatment in the past 12 months than those aged 12 to 25 years and 35 years and up.

The findings of the present study uphold the findings of Wu et al. (2016) and Lapham et al. (2020), who found that adolescents underutilized opioid-specific treatment. All three studies utilized secondary data sets. The findings of this study aligned with the literature, which identified young adult age as a predictor for increased treatment-seeking for prescription opioid use disorder.

The present study's results showed that male sex and lower levels of education were also positively associated with increased treatment-seeking. There were no published studies with which to compare these findings regarding sex and educational attainment as predictors of increased treatment-seeking among the rural population; therefore, this population requires further investigation. The current research's findings suggest the importance of continuously targeting rural Americans for NPOU, POM, and treatment-seeking interventions. Focused intervention is especially vital regarding NPOU among the Black population, young adults, individuals with lower levels of education, people with health insurance coverage; POM for the Black population and adolescents; and treatment-seeking behaviors for young adults, males, and individuals with lower levels of education.

Interpretation of Findings in the Context of the Theoretical Framework

Bronfenbrenner developed the SEM based on the premise of systems thinking, postulating that it is critical to understand the ecological system as a whole to fully understand human development (Susser & Susser, 1996). The findings from the current study could suggest social determinants of health in rural American populations observable at several levels of the SEM. This study showed that Black race, younger age, lower levels of education, and health insurance coverage were positively associated with increased NPOU; Black race and younger age were positively associated with increased POM; and younger age, male sex, and less education were positively associated with increased treatment-seeking. It could prove beneficial to address reducing NPOU and POM at the adolescent and young adult stages by raising awareness of the importance of strictly following the guidance and instructions of the prescribing physicians. The first level of the SEM, the individual, refers to biology and the unique, personal experiences that result in a particular behavior, such as NPOU or POM (CDC, 2020). The present study showed that members of the sample population with lower levels of education reported NPOU. Positive influences at the individual level of the SEM could potentially inform opportunities for improvement at the SEM relationship level.

The second SEM level, relationship, pertains to a person's most intimate social groups, peers, family, and partners to identify how these connections impact the individual's behavior (CDC, 2020). At this level, the most effective prevention strategy comes from within the sphere of influence. Because education was a predictor of NPOU in this study, it could prove critical for individuals to learn about or know someone from within their social group who utilized education to improve their circumstances. In the present study, rural American participants with lower levels of education reported NPOU.

The third level of the SEM is the community, comprising the environment in which individuals cultivate relationships, such as school, workplace, or neighborhood (CDC, 2020). NPOU and POM prevalence indicate a significant opportunity for health interventions in rural American communities. Wu et al. (2016) noted that the majority of individuals with opioid use disorder did not access appropriate treatment. This finding indicates a dire need for the community, such as workplaces and neighborhoods, to develop programs and policies that foster an environment where treatment-seeking is an accepted cultural norm. The present research showed that NPOU and POM rates could increase based on Black race, younger age, less education, and health insurance coverage. The community could achieve a great impact by implementing prescription opioid educational programming in predominantly Black neighborhoods, youth groups, and schools and partnering with local primary care providers.

Finally, the fourth level of the SEM is societal, where an individual examines behavior through a systematic lens. At the forefront of the societal level, cultural norms lead to behaviors, such as NPOU and POM, as a coping mechanism. Societal components involve policies that support economic, resource, and social disparities (CDC, 2020). Effective policies that can reduce NPOU and POM in rural U.S. communities would address overprescribing by clinicians, inadequate ability to recognize opioid misuse, and a lack of policies to ensure treatment for individuals in need.

Limitations of the Study

A study's limitations are elements of the methodology or design that could influence the findings, generalizability, application, utilization, and ability to establish internal and external validity (University of Southern California, 2020). This study used secondary data from the NSDUH, a comprehensive data set created from an audio computer-assisted self-interviewing process. Respondents could have chosen not to respond to each survey question, leading to missing data. Missing data from the original survey could reduce the reliability of results and skew inferences from the present study. The NSDUH utilized imputation to address missing data, which SAMHDA (2019) defined as replacing missing values with valid values. Statistical imputation in this study was necessary to derive an estimated value for the missing value from the available respondent-provided values.

The data came from a survey of a randomized household sample. SAMHDA (2019) defined a household as a civilian noninstitutionalized residence (including civilians residing on a military base, college dormitories, group homes, homeless people in shelters, and long-term residents of single rooms in hotels). A household sample may not be representative of substance users who experience housing instability. Because the NSDUH data are self-reported, they are susceptible to response bias, underestimation, or overestimation (Lavrakas, 2008). In addition, respondents might not have been entirely forthcoming, especially given the sensitive topics. The survey creators addressed this limitation by ensuring confidentiality through an audio computer-assisted self-interviewing process. Last, variables of interest not used in this study could have contributed to internal validity and indicated cause and effect. For example, as previously mentioned, the focus of the current analysis was on the rural population, and perhaps there is an interaction between urban/rural residency with regard to NPOU, POM, and treatment-seeking behaviors. However, this analysis was only of rural persons and, therefore, did not address urban-versus-rural differences.

Recommendations

There is a need to conduct additional research using rural American populations. It is necessary to further explore other substance use behaviors among rural Americans, especially since this population could be as much as or more susceptible to substance use, misuse, and overdose than their urban and metropolitan counterparts. As mentioned, 80% of those living with opioid use disorders do not receive treatment (Partnership to End Addiction, 2015). More education is needed regarding the benefits of treatment to the public in general and rural Americans in particular.

Black race was significantly associated with NPOU in the current study, with Black participants more likely than White and Hispanic respondents to have used pain relievers without their own prescription in the past 12 months. Also, with regard to POM, Black participants had higher odds than White and Hispanic respondents to have used pain relievers in a way other than directed in the past 12 months. Therefore, it would be beneficial for public health practitioners to conduct effective outreach with all races. Younger age was positively associated with increased NPOU, with greater odds for participants 18 to 25 years and 26 to 34 years to have used pain relievers without their own prescription in the past 12 months than persons aged 12 to 17 years and 35 years and older. Specific to POM, participants 12 to 17 years had greater odds than those 18 years and above to have used pain relievers in a way other than directed in the past 12 months. Also, treatment-seeking participants 26 to 34 years had greater odds than those 12 to 25 years and 35 years and up to have received alcohol or drug treatment in the past 12 months. Therefore, it would be beneficial for public health practitioners to conduct effective outreach to young adult rural Americans regarding prescription opioids and treatment-seeking behaviors.

Because male sex was positively associated with increased treatment-seeking, with men 1.93 times the odds as women to have received alcohol or drug treatment in the past 12 months, public health practitioners should conduct effective outreach to rural women. Less education was positively associated with increased NPOU. Participants who had completed less than high school, high school, or some college had greater odds than those with an associate degree and college graduates to have used pain relievers without their own prescription in the past 12 months. Regarding treatment-seeking, participants who had completed less than high school, high school, or some college had greater odds than individuals with an associate degree and college graduates to have received alcohol or drug treatment in the past 12 months. Therefore, it would be beneficial for public health practitioners to conduct effective outreach for NPOU and treatment-seeking to rural residents with lower levels of education. Finally, because insurance coverage status was positively associated with increased NPOU—participants covered by health insurance were more likely than those without coverage to have used pain relievers without their own prescription in the past 12 months—public health practitioners should conduct effective outreach to rural residents with health insurance coverage.

These outreach and education efforts can assist with increased knowledge and awareness of NPOU, POM, and treatment-seeking. While the current study included analysis of covariates analyzed in other studies, there were additional variables not investigated. Polydrug use was not studied and should be a subject for future studies.

Implications

Research, policy, and practice can collectively impact quality of life and improve public health, resulting in positive social change. Additional research is necessary to address why certain sociodemographic factors are associated with NPOU, POM, and treatment-seeking. Moreover, public health advocates should guide the dialogue in the rural community related to NPOU, POM, and treatment-seeking. According to Lippold et al. (2019), in terms of policy, a focus on regulatory practices for controlled substances, reform for criminal justice policies, increased numbers of treatment facilities, program development for stigma reduction, and safer prescribing practices could prove beneficial. This research supports the need for evidence-based approaches to reduce opioid prescribing, prevent opioid misuse, and treating of opioid use disorder. Several policies can be implemented at the state level to aid with this effort. Policies that govern trauma-informed treatment and address the family unit as a whole can assist with mitigating a cycle of substance use disorder. State policy can also mandate the consultation of a drug monitoring program for prescribers who prescribe opioids. Each state can utilize licensure and continuing education units to ensure providers are properly trained in safe prescribing practices. Finally, it could prove beneficial for the state to leverage policies and resources that address opioids across agencies such as public health, law enforcement, behavioral health, offices of substance use services, Medicaid, Governor’s offices, and social services. With state encouragement of a collaborative and multidisciplinary effort, there is potential for improved targeting of interventions, surveillance, and data sharing.

Positive Social Change

The SEM was an appropriate theoretical foundation for this research to identify the necessity for a comprehensive approach to addressing NPOU and POM of the rural U.S. population at multiple levels. This study's findings can contribute to positive social change within the rural community and the public health field. If race, age, sex, education, and health insurance status impact NPOU, POM, and treatment-seeking knowledge, it is imperative to educate rural Americans, especially those of the identified race, age, sex, education, and health insurance statuses. The findings of this study provide information to help communities understand the impact of NPOU, POM, and treatment-seeking behavior within the rural population. Policies developed based on the study could ensure equitable practices for this vulnerable population by preventing opioid misuse and increasing access to treatment. Finally, more targeted interventions could help increase treatment-seeking rates and decrease NPOU and POM overdose deaths among the rural population. Given the prevalence of NPOU and POM in the rural American community, this study raises critical concerns on the need for improved education and outreach. Future targeted public health education interventions should include partnerships with health care providers and pharmacies that can assist with the implementation of policies and practices.

Conclusion

The significance of this research was to raise awareness and education of the necessity for cultural and behavioral changes regarding NPOU, POM, and treatment-seeking. There is a need to continuously target rural Americans for NPOU and POM prevention and provide equitable access to treatment. It is critical to continue prescription opioid research and propose practical and political recommendations to prevent NPOU and POM and encourage treatment-seeking behaviors. Given the effectiveness of prescription opioid treatment, it is concerning that the majority of those who live with opioid use disorders do not access treatment. This finding provides an overview of the current climate and opportunities for improvement in the country's health system. The prevalence and mortality rates of prescription opioid overdoses require direct address. Future studies incorporating the SEM may prove beneficial, specifically among rural Americans. Such research will allow for a more concise understanding of opioid misuse at the societal level, highlighting the sociodemographic factors of race, age, sex, education, and insurance coverage status that create an environment conducive to opioid misuse and barriers to treatment-seeking among the rural population. Cultural and societal norms and contributing factors to health inequities merit consideration to identify factors contributing to NPOU, POM, and overdose deaths among rural Americans. Public health education interventions and programs that focus on increasing knowledge of NPOU and POM are necessary steps toward positive social change.

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