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A SPATIAL INQUIRY OF THE U.S. OPIOID EPIDEMIC AND GEODEMOGRAPHIC SEGMENTATION SYSTEMS

by

Ryan Baxter Hanson

A Dissertation

Submitted in Partial Fulfillment of the

Requirements for the Degree of

Doctor of Philosophy

Major: Earth Sciences

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I would like to thank the members of my committee for their guidance and time during the writing of this dissertation. I would like to give special recognition to my committee chair Esra Ozdenerol for her patience, academic guidance, and friendship. Without her, this dissertation would not have been possible.

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Abstract

Hanson, Ryan Baxter. Ph.D. The University of Memphis. May 2020. A Spatial Inquiry of the U.S. Opioid Epidemic and Geodemographic Segmentation Systems. Major Professor: Esra Ozdenerol, Ph.D.

The objective of this dissertation research was to explore the use of geodemographic segmentation as a socioeconomic variable to spatially analyze opioid related mortalities and hospital discharges. Opioid data were investigated by three ICD-10 classifications: heroin, other opioids, and other synthetic narcotics. Demographic and spatial characteristics of opioid mortality were examined using data from the Centers for Disease Control's (CDC) National Vital Statistics System mortality (NVSS-M) multiple causes of death dataset via the WONDER database for the year 2017. This was followed by a literature review of previous research that investigated the use of geodemographic segmentation systems in health research.

Spatial rules association data mining was used to explore the relationship between county level ESRI Tapestry segmentation and opioid mortality rates from the CDC NVSS-M for the years 2015-2017. These findings were further examined by comparing the results to the 2017 Tennessee opioid mortality and Tapestry data at the ZIP code level. Additional demographic analysis was conducted using county level socioeconomic variables, unemployment, and opioid prescribing rates.

Tennessee opioid related hospital discharge and mortality data from the year 2017 were analyzed using rate mapping, ANOVA, descriptive statistics, and spatial rules based association data mining. The rates were associated with ESRI Tapestry LifeMode groupings. The results of the analysis of Tennessee's ZIP code level data were compared to the CDC's county level data from 2017 to examine scale dependency of the analysis and data.

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Chapter 1 Dissertation Introduction

The United States has grappled with an opioid drug epidemic that has evolved over the last two decades. In 2017, an average of 130 Americans died every day from opioid drugs, and the rate of overdose deaths due to opioids was six times higher than it was in 1999, the earliest year of data available from the Centers for Disease Control (CDC) (CDC, 2018a). This dissertation consists of a series of chapters to be submitted for publication as a book chapter and journal articles. In Chapter 2, opioid related mortality data from the CDC were used to investigate the demographics of the epidemic and challenge the notion of the opioid crisis being predominately associated with white, rural, middle-aged males. While some aspects of the notion were true, this idea was found to be an oversimplification that fails to take into account the historical development of the opioid crisis, which has involved multiple classes of opioid drugs, and the latest research that is seeing an increase among females and minorities.

Three classes of opioids were investigated as part of the research: heroin, other opioids (prescription opioids), and other synthetic narcotics (synthetic opioids). The research in the first chapter and the remainder of the dissertation found that heroin was more associated with urban environments, other opioids were prevalent in both urban and rural areas but more so in rural, and other synthetic narcotics were associated with areas where synthetic drugs such as fentanyl were used as adulterants in the illicit drug supply. The chapter two will be published as a book chapter in a publication exploring spatial gender inequalities.

Chapter 3 focused on the use of geodemographic segmentation systems for health care research. Geodemographic segmentation is data typically used for marketing purposes to identify consumers' lifestyles and preferences. The chapter consisted of a literature review of previous research that used geodemographic segmentation systems as a means for health care related studies and will be submitted for publication in the *International Journal of Environmental Research and Public Health*. The purpose of this research was to develop an understanding of how these systems have previously been used. The following two chapters investigated how ESRI Tapestry geodemographic segmentation data could be used as a socioeconomic variable for investigation of the opioid epidemic.

The fourth chapter also used opioid mortality data from the CDC at the United States county level to explore the use of geodemographic segmentation to study the epidemic. Different segmentations were found to be associated with high levels of opioid mortality based on drug classification at the county level using spatial rules based association data mining. These associations were further investigated using descriptive statistics of other publicly available demographic variables and Tennessee Department of Health mortality records. It was found that ESRI Tapestry data were better for describing rural populations than urban due to the homogeneity of the population in rural areas. Urban counties' populations were too diverse to be adequately described using Tapestry data at the county level. This showed how these techniques can have limitations for describing heroin mortality since it is an urban drug.

The fourth chapter also used the findings to demonstrate how geodemographic segmentation systems could be used to conduct more efficient interventions, preventions, and treatments. This was done by using segmentations identified in the chapter's analysis and ESRI Tapestry documentation to suggest strategies based on lifestyle preferences.

Chapter 4 will be submitted for review for publication to the *International Journal of Health Geographics*.

Chapter 5 continued with this research into geodemographic segmentation but focused on hospital discharge and mortality rates at the ZIP code level in Tennessee. This chapter will also be submitted for publication in *the International Journal of Health Geographics*. First, maps were created to visualize the clustering of discharge and mortality rates across the state. This was followed by ANOVA and descriptive analysis of hospital discharge and mortality rates by ESRI Tapestry LifeMode groups. LifeModes were identified that had high opioid hospital discharge and mortality rates. The rates by ZIP code were further investigated using spatial rules based association data mining. These results supported the finding of the descriptive analysis of LifeModes associated with high rates and identified those correlated with low rates.

Descriptive analysis and spatial rules based association data mining were conducted using mortality data at the United States county level. The results of this analysis were somewhat different than the findings for the state of Tennessee. These differences were used to demonstrate scale dependency.

The analysis in the fith chapter pointed toward the findings in earlier chapters of the dissertation that heroin was predominately an urban drug. Prescription opioids were abused in both urban and rural areas but had higher rates in rural areas. Synthetic opioids were more random but were related to areas where the drugs had been used as an adulterant in illicit drugs.

The final chapter of the dissertation contains a synopsis of the findings of the chapters mentioned above and presents future implications.

Chapter 2 The Evolving American Opioid Crisis: An Analysis of Gender, Racial Differences, and Spatial Characteristics

Introduction

The United States is in the midst of an opioid crisis that has developed over the last 30 years. The epidemic is part of a larger trend of drug abuse in which annual rates of drug overdoses have increased exponentially since the 1980s (Jalal et al., 2018). In 2017, 67.8 percent of drug overdoses were attributed to opioids, which accounted for 47,600 deaths (Scholl, 2019). Between 1999 and 2017, there were almost 400,000 opioid-related deaths, and opioid overdose deaths were six times higher in 2017 than in 1999 (CDC, 2017). Between 2016 and 2017, the unintentional overdose mortality rate involving synthetic opioids rose 45.5 percent (5.5 to 8.0 deaths per 100,000) (CDC, 2017).

The opioid epidemic has a complex demography affected by gender, age, race, urbanicity, the opioid drug in question, historical developments, and location. It cannot easily be designated to one set of demographic components that describe individual victims (Dasgupta et al., 2018; James & Jordan, 2018; Kolodny, 2017; Moran, 2018; Phillips et al., 2017; Shihipar, 2019). It is an oversimplification to assign one demographic profile to the epidemic. None the less, media coverage and policy-makers have focused on the rise of deaths among male, white, middle-aged, middle-class, rural, and suburban users (Dasgupta et al., 2018; James & Jordan, 2018). The epidemic has impacted multiple races in varying locations. Recently, new classes of opioids have begun to cause increases in mortality that have impacted younger groups in more urban environments (Phillips et al., 2017; Scholl, 2019).

This chapter examines the gender differences and spatial evolution of the opioid epidemic. The history of the epidemic is explored in relation to the CDC's National Vital Statistics System mortality (NVSS-M) multiple causes of death dataset via the WONDER online database (CDC, 2017). The data are used to highlight the impact the epidemic has had in relation to various demographics such as age, gender, and race by location based on varying opioid classifications used in the database.

Classifying Opioids

Opioids are a broad class of drugs that are prescribed for the treatment of pain and can be abused recreationally (Krieger, 2018). There are several basic types of opioids, which include natural opioids derived from the resin of the poppy plant, such as morphine and codeine; semi-synthetic opioids such as hydrocodone, oxycodone, or buprenorphine; and fully synthetic opioids which are created in a laboratory and include drugs such as fentanyl and methadone (Opiate Addiction and Treatment Resource, 2013). Synthetic opioids can be 50 to 100 times as potent as the natural opioid such as morphine (HHS, 2017).

Prescription opioids are those prescribed by a physician for pain management and can be natural, semi-synthetic, or synthetic (Hall et al., 2006). Prescription opioids can also be prescribed for the treatment of opioid addiction (Hall et al., 2006). Methadone and buprenorphine are two opioids used in this way (Hall et al., 2006). Table 1 below contains a list of the general classifications of opioid drugs with examples of each type.

Table 1. General Classification of Opioids

Classification	**Examples**
Natural Opioids	Morphine and Codeine
Semi-synthetic Opioids	Hydrocodone, Oxycodone, and Buprenorphine
Full-Synthetics Opioids	Fentanyl and Methadone
Prescriptions Opioids	Opioid Drugs Obtained with Physician's Prescription
Illicit Opioids	Opioids Obtained without Physician's Prescription

In contrast to prescription opioids, illicit opioids are those obtained without a prescribing physician. These can come in many forms, such as the semi-synthetic opioid heroin which is derived from morphine, illegally obtained prescription opioids, counterfeit opioids, and drugs adulterated with synthetic opioids such as fentanyl (Hall et al., 2006).

The CDC classifies opioids under the following International Classification of Diseases, 10^{th} Revision (ICD-10), categories: opium (T40.0), heroin (T40.1), other opioids (T40.2), methadone (T40.3), and other synthetic narcotics (T40.4) (CDC, 2018b). The CDC classifies prescription opioid deaths as those caused by natural and other opioids (T40.2) and methadone (T40.3) (CDC, 2018b). Table 2 below contains details of the opioid classifications by the ICD-10.

Table 2. Centers for Disease Control ICD-10 Opioid-Related Classifications

ICD-10 Code	ICD-10 Title	Description	Code Type
X-40 - X-44	Drug Poisonings (Overdose) Unintentional	Accidental Overdoses	Underlying Cause of Death
T40.0	Opium	Opium	Multiple Cause of Death
T40.1	Heroin	Heroin	Multiple Cause of Death
T40.2	Other Opioids	Natural and Semi-synthetic Opioids	Multiple Cause of Death
T40.3	Methadone	Methadone	Multiple Cause of Death
T40.4	Other Synthetic Narcotics	Synthetic Opioids	Multiple Cause of Death

History of the Opioid Crisis

According to the CDC, the opioid crisis occurred in a series of three waves that were all associated with different classes of opioids (CDC, 2018a). The first wave had its roots in the 1980s but started to take shape in the 1990s as physicians increased the prescribing of opioid pain relievers (Kolodny et al., 2015). During the 2000s, the crisis became a public health epidemic as mortality rates began to rise.

The second wave began in 2010 and was associated with a rise in mortality due to the illicit drug heroin (Rudd et al., 2016; Spencer et al., 2019). This was followed by the third wave which saw an increase in mortality from synthetic drugs, such as fentanyl, which were used to adulterate illicit drugs like heroin, counterfeit pills, and cocaine (Scholl, 2019; Spencer et al., 2019). Figure 1 below shows the overall U.S. mortality rate due to opioids, while Figure 2 shows the mortality rate divided into different classes.

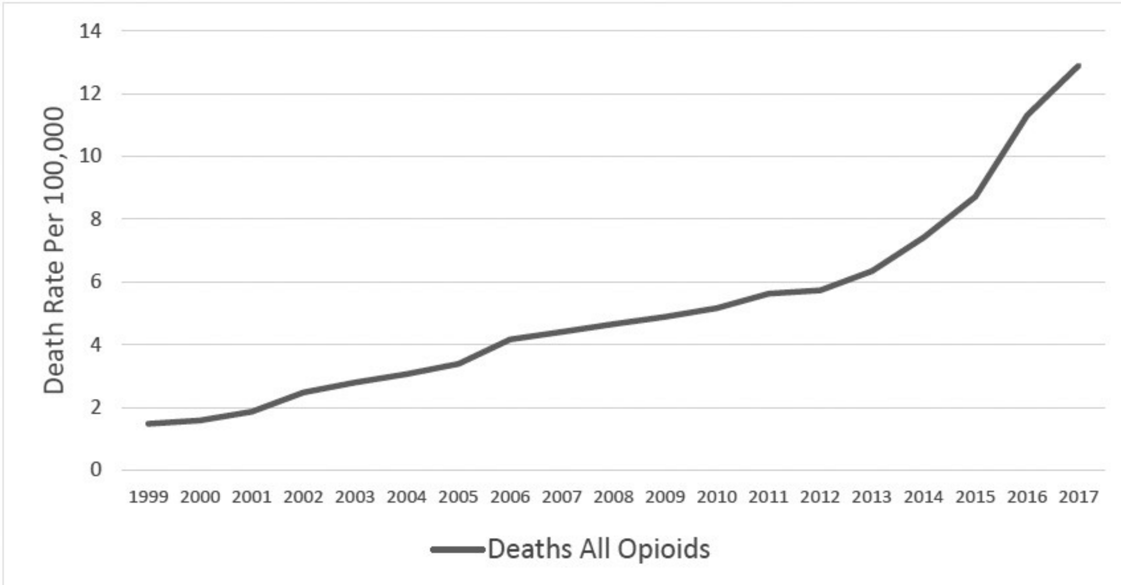

Figure 1. U.S. Annual Rate of All Opioid Overdose Mortalities, 1999-2017

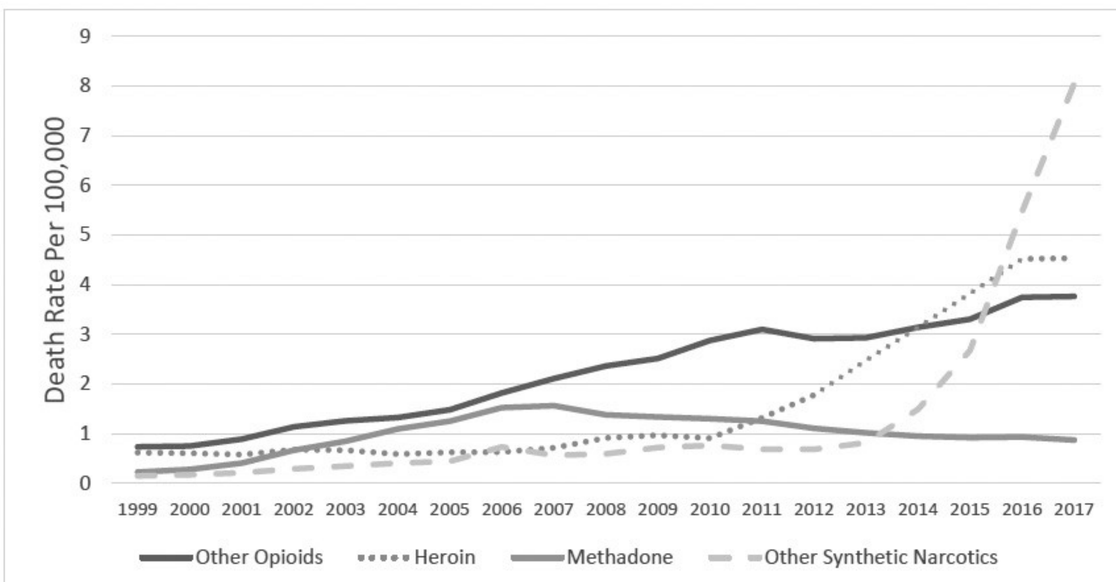

Figure 2. U.S. Annual Rate of Opioid Overdose Mortalities by Opioid Type, 1999-2017

The first wave of the opioid epidemic has a complex history with multiple causes that include, but are not limited to, questionable academic research, changing practices and opinions on pain management, lobbying by pharmaceutical companies, misinformation from nonprofit organizations backed by the pharmaceutical industry, and aggressive marketing tactics to physicians (DeShazo et al., 2018; G. H. Jones et al., 2018;

Meldrum, 2016). In 1980, Dr. Hershel Jick published a letter in the *New England Journal of Medicine,* after reviewing the cases of 11,882 hospitalized patients who received opioid treatments for pain, in which he concluded that "the development of addiction is rare in medical patients with no history of addiction" (Porter & Jick, 1980). The letter became a landmark study that was cited 608 times between 1980 and 2017 (DeShazo et al., 2018; G. H. Jones et al., 2018). Additionally, Dr. Kathleen Foley published two articles in 1981 and 1986 that along with Jick's one-paragraph letter became the basis for a 20-year campaign promoting long-term opioid use for the management of chronic, noncancer-related pain (Meldrum, 2016).

Purdue Pharma released the prescription opioid MS Contin in 1984, followed by OxyContin in 1995, which was marketed as a less addictive opioid (DeShazo et al., 2018). The American Pain Association, which received large portions of its funding from Purdue Pharma, proposed the concept that pain be measured as the fifth vital sign in 1995, an idea which went on to be supported by the Veterans Affairs Medical System, the Joint Commission, the American Medical Association, and the American Academy of Family Physicians (DeShazo et al., 2018; G. H. Jones et al., 2018). It was this ideology that spurred physicians to prescribe opioids at increasing rates. Throughout the 2000s, opioid prescription rates and overdose deaths increased. However, this trend began to change in 2010 with the onset of the second wave of the crisis (Hoots et al., 2018). The rate of opioid prescriptions per 100 persons dropped 3.9 percent annually between 2010 and 2014 and decreased 10.5 percent annually from 2014 to 2017 (Hoots et al., 2018).

The second wave of the epidemic associated with heroin took effect as mortality rates from prescription opioids leveled off in 2010. Figure 2 below shows the U.S. annual rate of opioid overdose mortalities by opioid type. One explanation for the reduction in prescription opioid deaths is the introduction of more restrictive prescription drug monitoring programs (PDMP) that limited opioid prescribing and reduced the availability of prescription opioids for misuse and diversion into illicit drug markets (Bachhuber et al., 2019; Grecu et al., 2019; Strickler et al., 2019).

The restrictions placed on prescribing doctors and a lack of prescription drugs available for clandestine use may have led opioid abusers to the cheaper illicit alternative heroin. Prescription opioid abusers have been documented to switch to illicit drugs when prescription opioids are no longer available (NIDA, 2018). It is estimated that 4.0 to 6.0 percent of people who abuse prescription opioids transition to heroin and that 80.0 percent of heroin users first abused prescription opioids (NIDA, 2018).

However, the correlations between PDMPs and opioid deaths have varied by state. Research which evaluated the impact of PDMPs on mortality found a correlation between implementation and increased mortality from illicit opioids in certain states (Nam et al., 2017). Other research has shown that the effects of PDMPs on opioid mortality have been less conclusive (Fink et al., 2018). The inconclusive effects of PDMPs may be due to differences in the regulatory aspects of each individual state's program. It may also be attributed to differences in the availability of certain drugs among different illicit drug markets (Carroll et al., 2017; Ciccarone, 2017b).

The third and current wave of the opioid crisis was associated with the adulteration of illicit drugs with synthetic opioids such as fentanyl beginning in 2013. This was associated with increases in heroin use and demand and the introduction of illicitly-manufactured fentanyl (Ciccarone, 2017b). The increased use and demand saw the introduction of heroin being adulterated with fentanyl.

Gender of Opioid Mortality in Relation to Age, Race, and Ethnicity

The CDC's National Vital Statistics System mortality (NVSS-M) multiple causes of death dataset can provide insight into the demography of the opioid epidemic. The CDC's online WONDER database allows users to delineate data by demographics such as age, gender, race, year, location, and urbanicity. Additionally, queries can be filtered to be specific to certain drugs.

The following analysis and figures focus on several types of opioid drugs as defined by ICD-10 classifications. All data were pulled using the underlying cause of death X-40 to X-44, which represents accidental drug overdoses. This excludes drug poisonings that were the result of suicide, homicide, or had an undetermined underlying cause.

Figures that present data for all opioid deaths use ICD-10 codes T.40 to T.44. This includes the opioid drug classifications opium, heroin, other opioids, methadone, and other synthetic narcotics. In addition to this combined grouping, three classifications are analyzed individually in this chapter. All data are presented using the most recent year of data available, 2017.

Figures 3–6 below illustrate opioid mortalities from the different opioid drug categories described above for different age groups by gender. A common aspect of the data that is seen in these figures, as well as the figures in the remainder of the chapter, is that the opioid epidemic had a greater impact on males than on females in terms of mortality. This greater rate of male mortality could be based on the tendency for males to be less risk averse (Charness & Gneezy, 2012; Pawlowski et al., 2008). Figure 3 presents the mortality rates for all opioids by age and gender. Male mortality rates peaked at ages 25–34, with a rate of 38.3 deaths per 100,000 males. This was followed by a steadily-decreasing rate for each ten-year age group. This goes somewhat against the idea that the impact was greatest among middle-aged males.

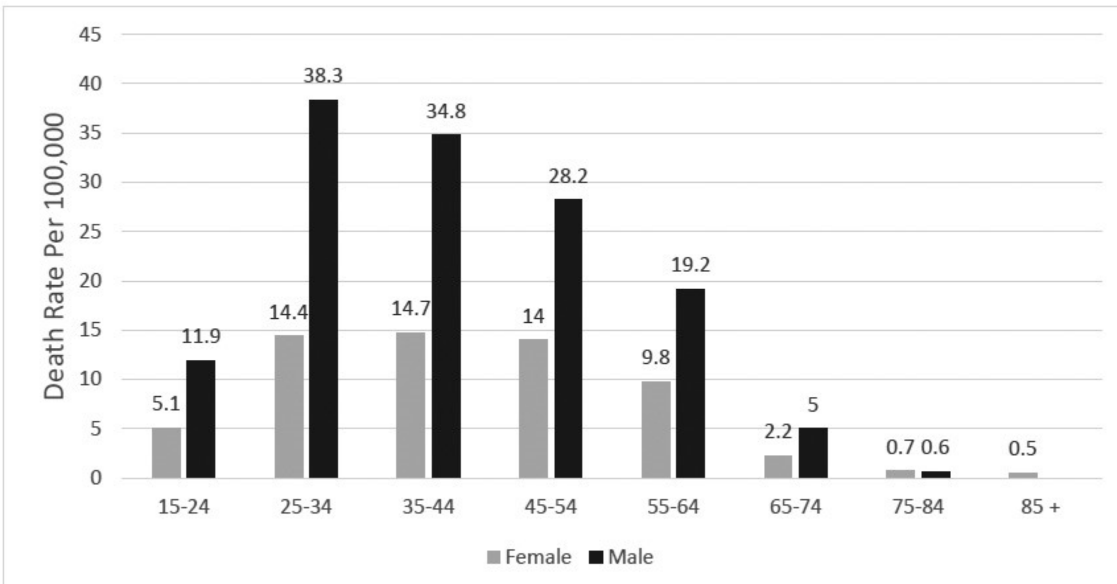

Figure 3. U.S. Rate of All Opioid Overdose Mortalities by Age and Gender, 2017

Female mortalities peaked later at ages 35–44 but had a more consistent rate of mortality between the ages of 25–54. This could be due to the lower number of mortalities among females but also shows that mortality among females from all opioids cannot be considered solely a middle-aged phenomenon. The data showed that mortality rates had become unreliable for males aged 85 and over but were represented for females. This is probably a result of differences in life expectancy between females and males.

Looking at each drug category individually provides further insight into opioid deaths. Figure 4 shows heroin-related mortalities for similar age categories as those shown in the previous figure. Heroin mortalities for both genders peaked at ages 25–34, with females at 5.2 and males at 15.3 deaths per 100,000 individuals. Both genders' mortality rates began to decrease with each age group. Like all opioid mortalities, deaths related to heroin decreased with age.

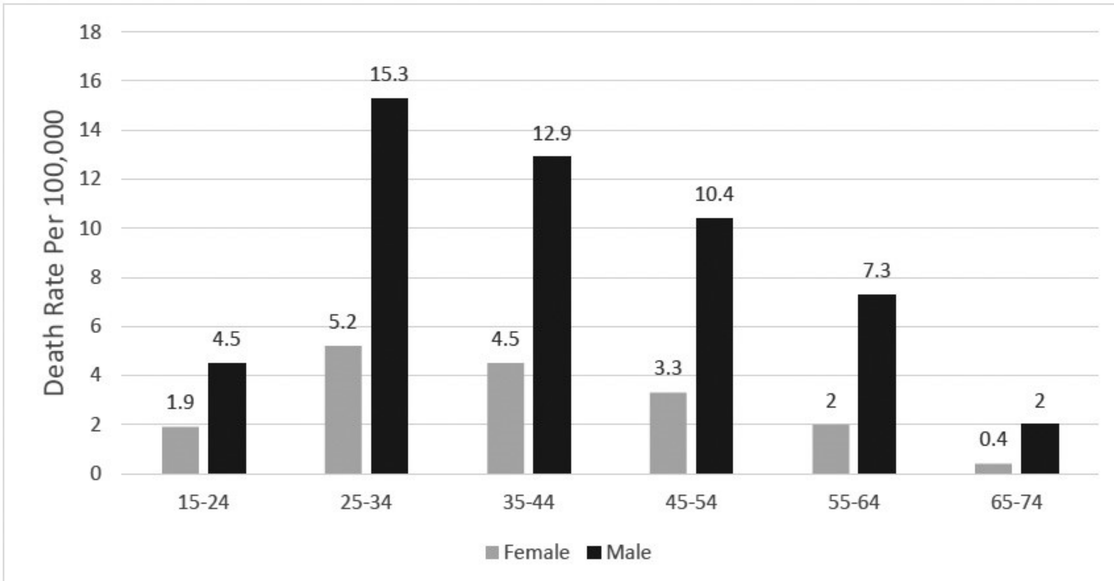

Figure 4. U.S. Rate of Heroin Overdose Mortalities by Age and Gender, 2017

However, data on other opioid mortalities show a stronger pattern of association with middle-aged mortality than did heroin. These mortality rates are illustrated in Figure 5. The rates for other opioid deaths were lower than those for heroin in the 15–24 and 25–34 age groups in both genders. However, rates for other opioid deaths among females were higher than for heroin in the age groups between 35 and 64. This shows an association between middle-aged populations and prescription opioid abuse. Perhaps there is a preference for prescription opioids among the middle-aged due to greater access to health care and less access to illicit drug markets among older populations.

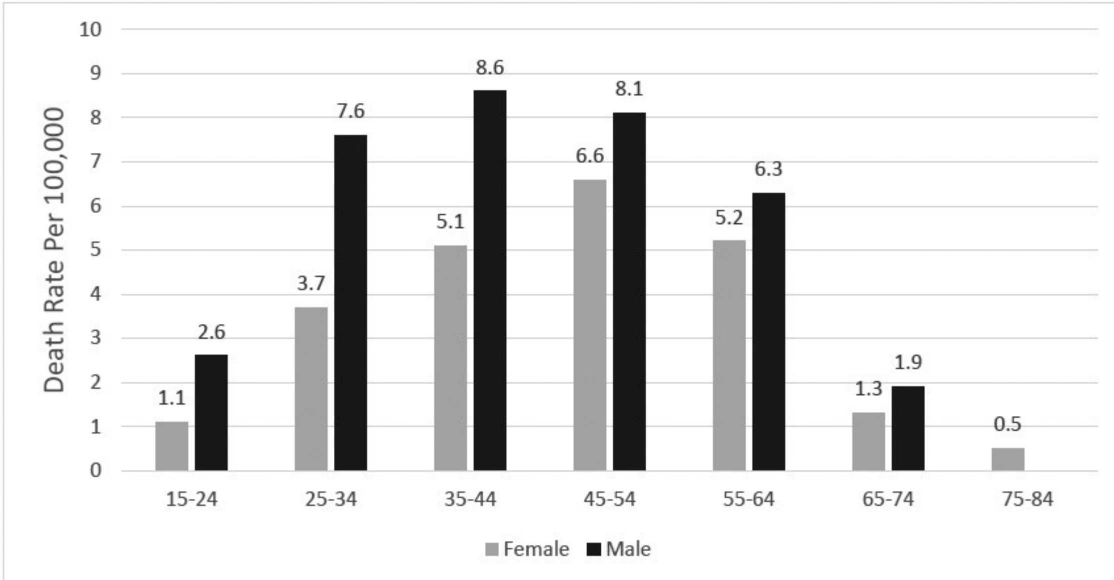

Figure 5. U.S. Rate of Other Opioid Overdose Mortalities by Age and Gender, 2017

In the female age groups of 45–54 and 55–64, the death rates from other opioids were double those for heroin. Male mortality rates from other opioids peaked at ages 35–44, while female mortality rates peaked at ages 45–54. The data suggest that heroin use is more common among younger individuals, particularly males, while other opioid misuse is present in both younger and older populations. Additionally, females are more at risk of mortality from other opioids than from heroin, particularly at ages 35–54. This may be attributed to females having more access to prescription opioids or more opportunities for introduction due to more frequent physician visits. It could also be due to females being more risk averse than are males and perceiving prescription opioids as less dangerous and more socially-acceptable drugs than illicit heroin.

The highest rates of mortality linked to an individual opioid drug classification were found in the data for other synthetic narcotics. Synthetic opioids' lethality relates to the strength of synthetic opioids in relation to other opioid classifications and the fact that synthetic opioids such as fentanyl are used as adulterants in heroin and other illicit drugs

(HHS, 2017; Mars et al., 2016; Phillips et al., 2017). Figure 6 shows the mortality rates from other synthetic narcotics by age group and gender. The pattern of mortality among age and gender in the figure mimics the pattern found in the heroin mortalities figure with the exception that the rates are higher. This suggests a correlation between fentanyl's use as an adulterant in heroin and mortalities related to synthetic opioids and heroin. Mortality rates for both genders peaked at ages 25–34 (males at 26.6 and females at 9.6 per 100,000). Like for heroin, the rates taper off with age, suggesting that heroin and illicit drugs adulterated with synthetic opioids are more commonly abused by younger individuals.

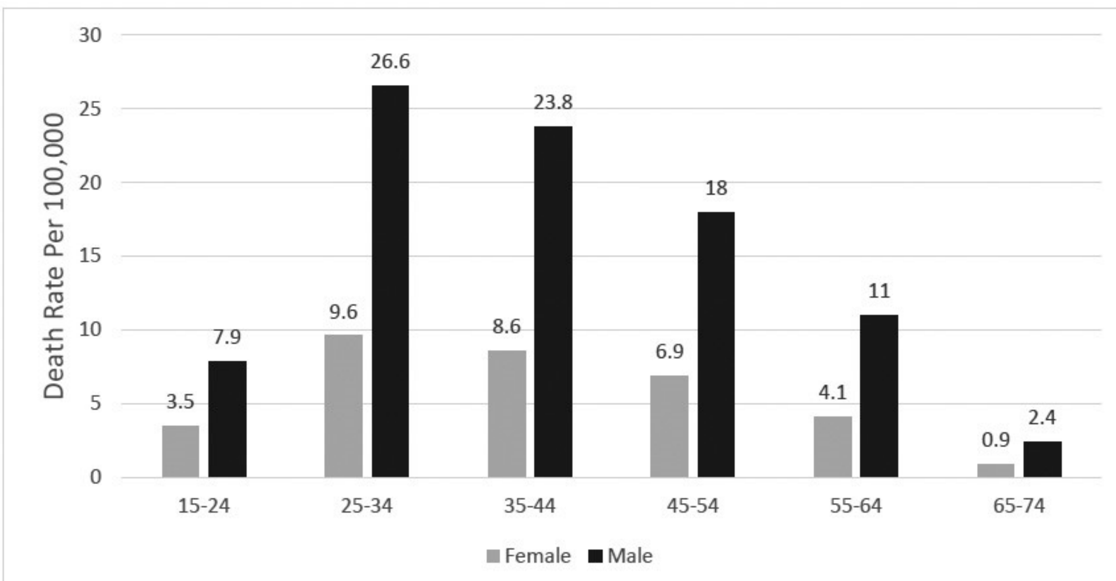

Figure 6. U.S. Rate of Other Synthetic Narcotic Overdose Mortalities by Age and Gender, 2017

It is important to note the differences in mortality rates among females when comparing other opioids and other synthetic narcotics. Females had a higher rate of mortality from other opioids in the 55–64 age group and a similar rate for the 45–54 group. This further shows the association between middle-aged females and prescription opioid abuse. Females are more likely to die from prescription opioids in middle age than from synthetic opioids which are many times more powerful.

Opioid mortalities by drug classification and by race and gender are presented below in Figures 7 to 10. Mortalities for all opioids by race and gender are represented in Figure 7. White males have the highest death rates from all opioids at 19.9 per 100,000 deaths, followed by African Americans at 16.0, and Native Americans at 11.0. However, there were no significant differences in mortality rates for females from all opioids among whites, African Americans, and American Indian or Alaska Natives. This further demonstrates how males regardless of race have been more greatly affected by the opioid crisis with regard to all opioids. Looking at the data for mortalities due to specific opioid classifications provides further insight into the impact regarding race and gender.

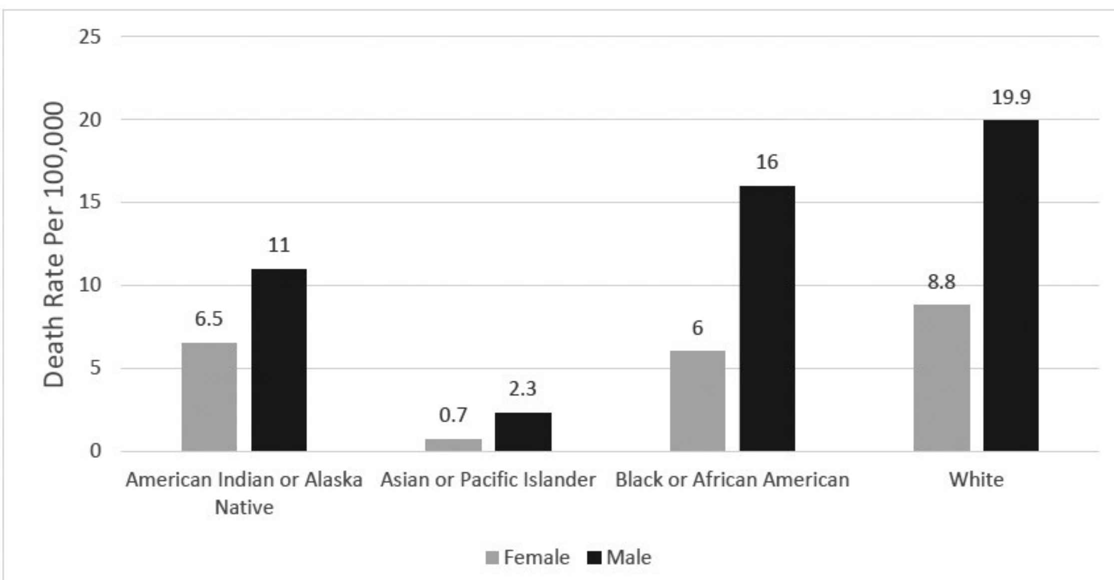

Figure 7. U.S. Rate of All Opioid Mortalities by Race and Gender, 2017

The next three figures present the mortality rates by race for individual opioid drugs. Figure 8 illustrates the death rates for heroin by race and gender. African American and white males had similarly high mortality rates at 7.1 and 7.4 per 100,000.

Asian, African American, and white females all had similar rates of heroin-related mortality (2.1, 2.2, and 2.4 per 100,000). A similar pattern of high rates among white and African American males from other synthetic narcotics is seen in Figure 9, white males at 12.9 and African American males at 11.7 deaths per 100,000. While female rates from other synthetic narcotics were comparably low for all races. The similar pattern of mortality between heroin and other synthetic narcotics mirrors the patterns seen for age and mortality shown in Figures 4 and 6. This further supports the association of heroin with synthetic opioid mortality.

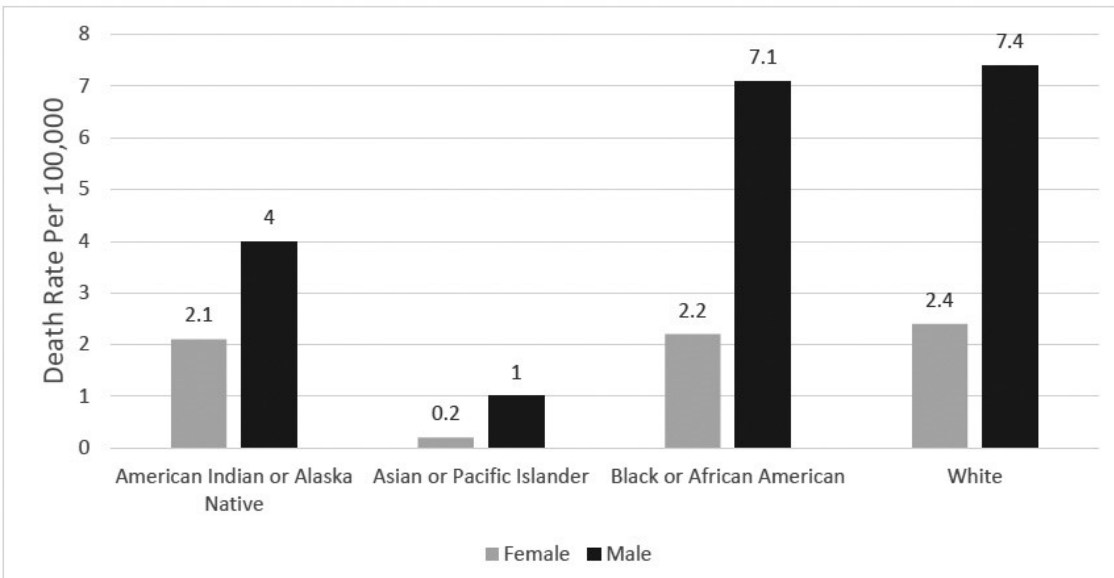

Figure 8. U.S. Rate of Heroin Overdose Mortalities by Race and Gender, 2017

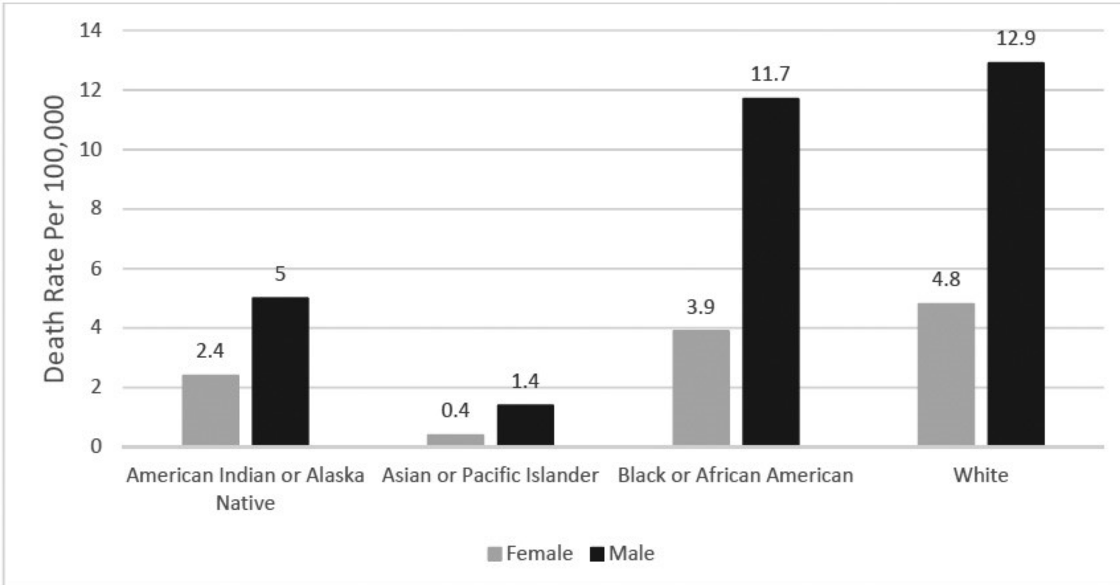

Figure 9. U.S. Rate of Other Synthetic Narcotic Overdose Mortalities by Race and Gender, 2017

Scholars have pointed out that health professionals and the media have falsely portrayed the opioid crisis as a predominately white, male, rural problem which ignored the fact that African Americans have been greatly impacted by the crisis as well (Alexander et al., 2018; James & Jordan, 2018; Shihipar, 2019). The data support this notion. A longitudinal investigation of the data shows that mortality rates for African American males from heroin have risen along with white male increases (Moran, 2018). On top of that, African Americans have been increasingly affected by the epidemic in more recent years. The percentage change of African American mortalities between 2015 and 2017 from all opioids and heroin was more than double that of whites (all opioids, 116.0 and 47.0 percent change; heroin, 43.0 and 12.0 percent change). Rates of synthetic opioid mortality for African American males grew 60.0 percent more than those for white males during the same time period (333.0 and 200.0 percent change). African American mortality rates have lagged behind white rates but have experienced larger increases in more recent years. This could be due in part to the introduction of fentanyl as an adulterant illicit drug.

The data are limited to the time period between 1999 and 2017. It would be beneficial to have rates from earlier periods to see how races were affected differently in the earlier years of the epidemic. It would also be helpful to compare different responses of policy-makers to earlier drug epidemics, such as the 1960s heroin and 1980s crack epidemics, which were considered to be associated with African Americans, to the responses to the current opioid epidemic (Cohen, 2015; Glanton, 2017).

Mortality rates attributed to other opioids by race, seen in Figure 10, show a different pattern than in the previous figures on race. White males had the highest rate of mortality with respect to both gender and race. Interestingly, the American Indian or Alaska Native race had higher mortality rates than did African Americans. One possible explanation for this could be that physicians are less likely to prescribe opioids to African Americans due to the racist stereotype that they are more likely to misuse or sell the drugs (Alexander et al., 2018; Lopez, 2016).

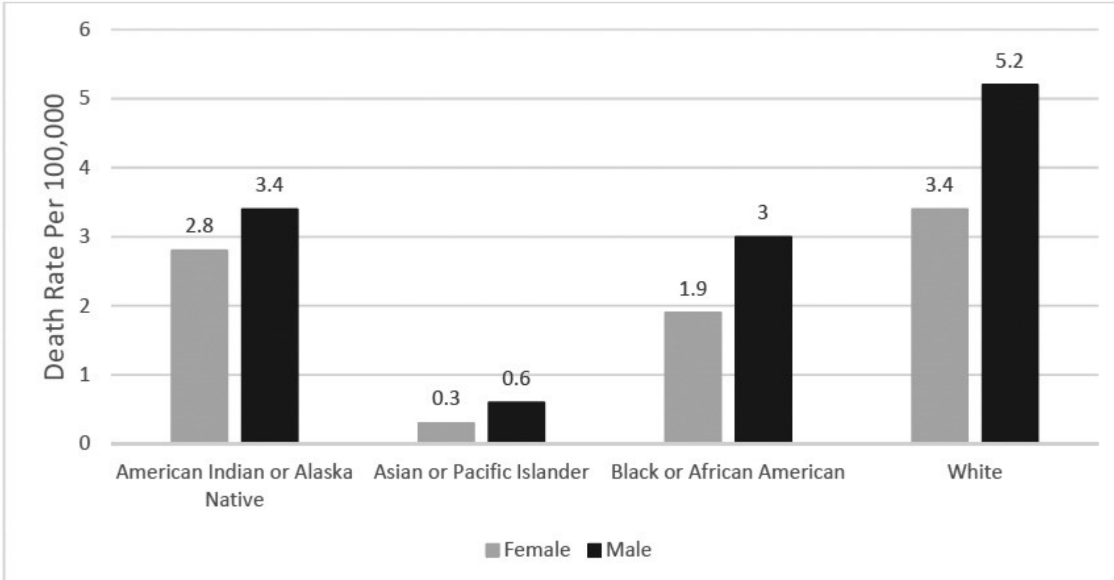

Figure 10. U.S. Rate of Other Opioid Overdose Mortalities by Race and Gender, 2017

It is important to note that Asian or Pacific Islander mortality rates were low in all opioids and the individual opioid classifications. This could be due to lower rates of drug abuse among Asian races. This can be supported by the data. A search for mortalities using the underlying cause of death codes for accidental overdoses (X-40-X-44) shows that Asian or Pacific Islanders had a much lower rate of mortality (3.1 per 100,000) than did other races regardless of the drugs that caused the mortality (whites, 20.4; Black or African American, 17.8; and American Indian or Alaska Native, 14.1 per 100,000).

In addition to race, the database allows for classification of mortality rates by ethnicity which accounts for two categories, Hispanic or Latino and Not Hispanic or Latino. Hispanic or Latino had much lower rates compared to Not Hispanic or Latino. The rates were less than half of those for Not Hispanic or Latino. However, even among Hispanic or Latino, males have significantly higher rates than do females. Male Hispanic or Latino mortality rates are 2.3 to 4.5 times higher than for females in studied opioid drug categories. This further shows that opioids had a larger impact on males than on females. Figure 11 illustrates these statistics.

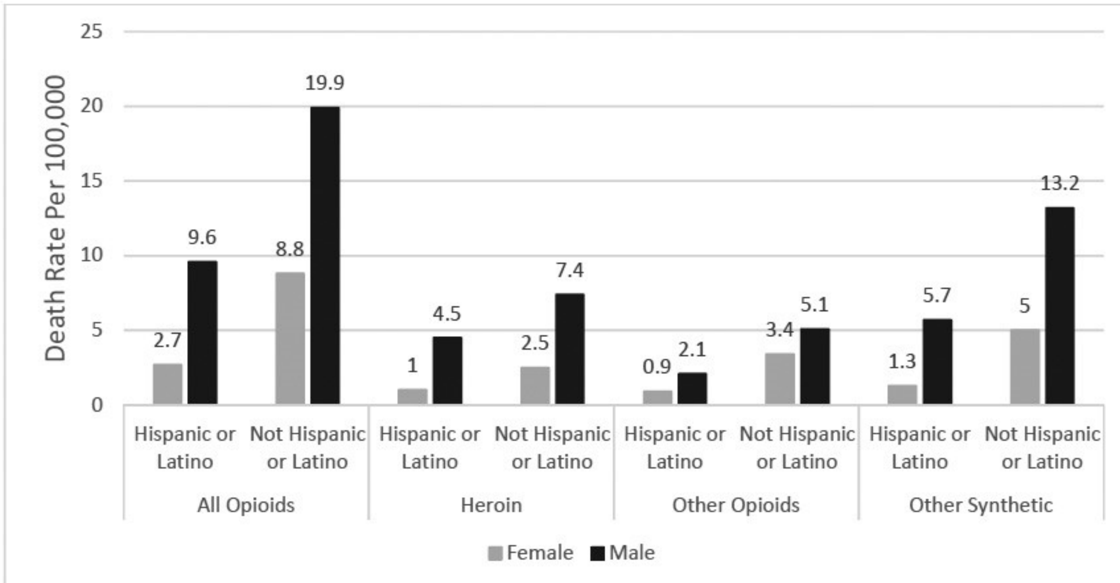

Figure 11. U.S. Rate of All Opioid Overdose Mortalities by Opioid Type, Ethnicity, and Gender, 2017

Urbanicity of Opioid Mortality

In addition to demographics, the CDC's WONDER database allows users to delineate mortalities based on the 2013 Urban-Rural Classification. This classification was created by the National Center for Health Statistics to study health differences among the urban-rural continuum (NCHS, 2019). The Urban-Rural Classification consists of six categories of urbanicity at the county level. Urbanicity is determined by whether a county is located within a metropolitan or micropolitan area and the county's population (Ingram & Franco, 2014). Table 3 below contains details about the rules and descriptions of the 2013 Urban-Rural Classification.

Table 3. 2013 Urban-Rural Classification

Level		Urbanization Level	Rule/Description
1	Metropolitan	Large Central Metro	Counties in MSAs of one million or more population that (1)Contain the entire population of the largest principal city of the MSA, or (2) Have their entire population contained in the largest principal city of the MSA, or (3) Contain at least 250,000 inhabitants of any principal city of the MSA
2		Large Fringe Metro	Counties in MSAs of one million or more population that did not qualify as large central metro counties
3		Medium Metro	Counties in MSAs of populations of 250,000–999,999
4		Small Metro	Counties in MSAs of populations less than 250,000
5	Nonmetropolitan	Micropolitan	Counties in micropolitan statistical areas
6		Noncore	Nonmetropolitan counties that did not qualify as micropolitan

Figures 12–15 below show the relationship between opioid overdose mortalities and urbanization classification and gender. Males have higher rates of mortality than do females in all urbanization categories for all opioid drug classifications. Figure 12 shows the mortality rates for all opioid drugs. The highest rate for male mortality from all opioids was found in Large Fringe Metros at 21.1 deaths per 100,000, and rates for males were highest in the three more urban categories. The female mortality rates were highest in the Medium Metro categories for all opioid drugs, but unlike the male rates, female rates were more consistent across the urban-rural continuum. The highest rates were among males in urban areas. This is most likely associated with heroin and other synthetic narcotic use. Examples of Large Fringe Metros are counties that tend to be suburban counties of a metropolitan statistical area such as Tipton County in the Memphis, TN-MS-AR statistical area or Dickson County in the Nashville-Davidson-Murfreesboro-Franklin statistical area. Medium Metros are counties also located in metropolitan statistical areas but with smaller populations such as Knox County in the Knox, TN statistical area or Hamilton County in the Chattanooga, TN-GA statistical area.

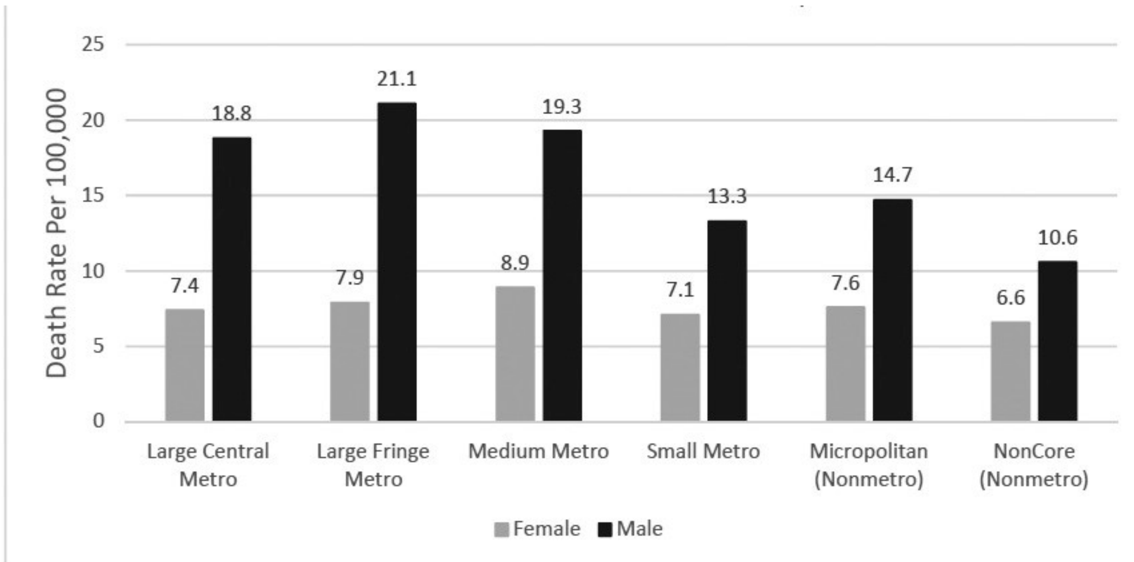

Figure 12. U.S. Rate of All Opioid Overdose Mortalities by 2013 Urbanization and Gender, 2017

The mortality rates from heroin and other synthetic narcotics are seen in Figures 13 and 14. Like in previous figures, there seems to be a relationship between these two drugs in that they both had their greatest impact in more urban areas. Again, this is most likely due to fentanyl's use as an adulterant of heroin.

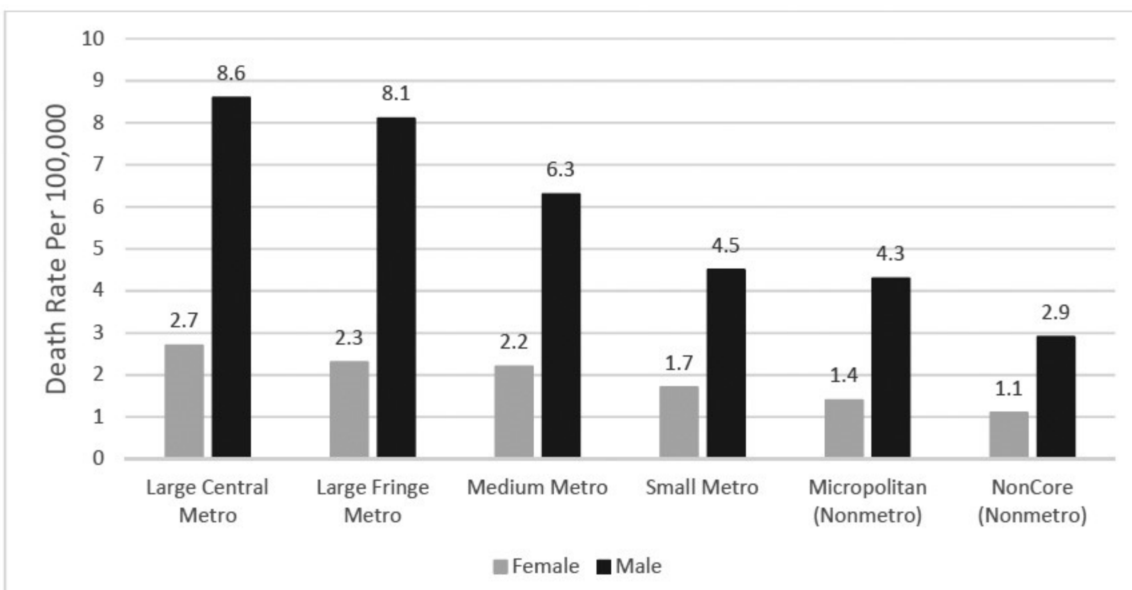

Figure 13. U.S. Rate of Heroin Overdose Mortalities by 2013 Urbanization and Gender, 2017

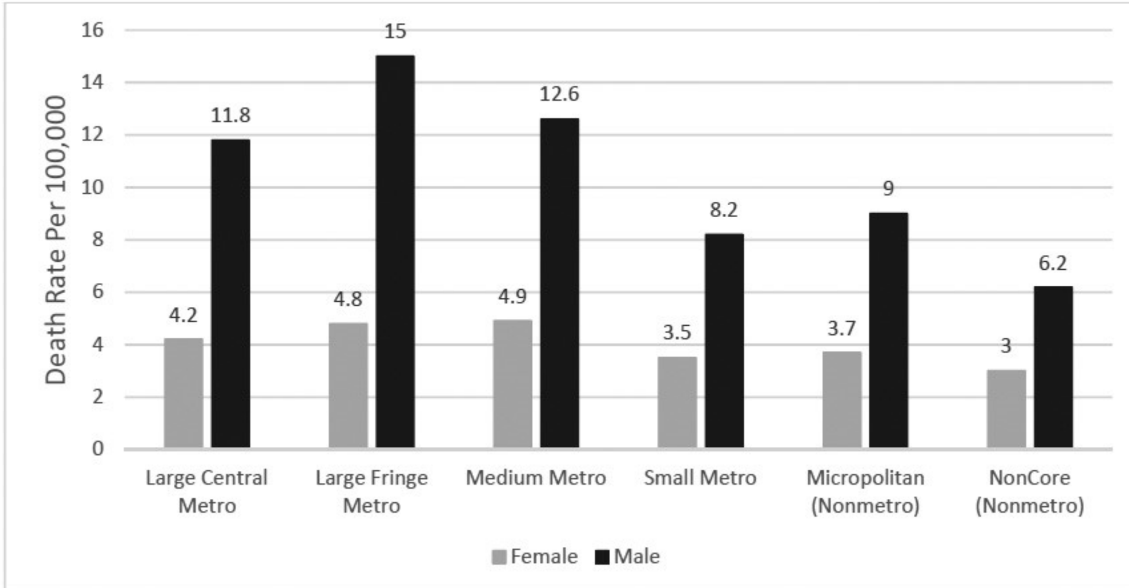

Figure 14. U.S. Rate of Other Synthetic Narcotic Overdose Mortalities by 2013 Urbanization and Gender, 2017

The mortality rates associated with heroin decreased for both genders as counties became more rural. However, males were more greatly affected by the drug. Other synthetic narcotic mortality rates showed a similar pattern, having a larger impact on male mortality. Like heroin, synthetic opioids had the highest mortality rates in urban areas. The peak mortality rate for males was 15 deaths per 100,000 in Large Fringe Metros, and the peak for females was 4.9 in Medium Metros. However, there was not the same constant decrease of mortality across the urban-rural continuum for other synthetic narcotics that was present in the data for heroin. These two drugs most likely had a larger influence in urbanized areas due to their use as an adulterant in heroin in urban drug markets. The presence of other synthetic narcotics in more rural counties may be associated with fentanyl's use as an adulterant in counterfeit prescription drugs.

Mortality rates associated with other opioids are illustrated in Figure 15. Males had the highest rates, but the rates for both genders were more random in relation to their urbanicity. There are high rates for both genders in both urban and rural classifications.

This goes against the notion of prescription opioids being more abused in suburban or rural settings. The term "hillbilly heroin" has been coined to describe the phenomenon of prescription drugs such as OxyContin being abused by individuals in rural areas due to the lack of accessibility to heroin. Research has shown that this stereotype is not true, and that city dwellers are just as likely to abuse prescription opioids as are individuals living in rural areas (Black & Hendy, 2019).

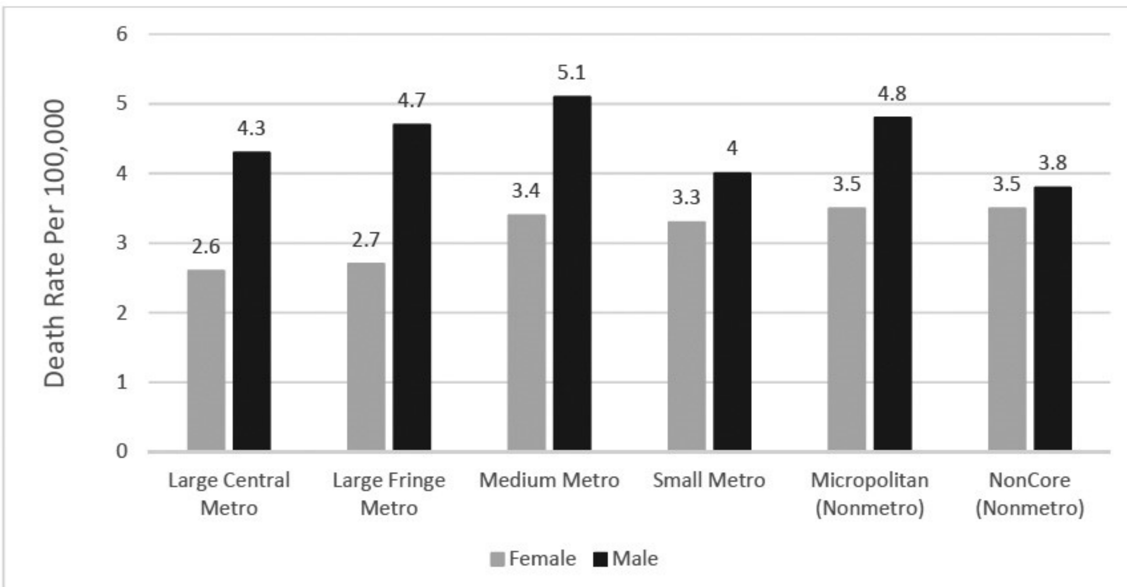

Figure 15. U.S. Rate of Other Opioid Overdose Mortalities by 2013 Urbanization and Gender, 2017

Spatial Aspects of Opioid Mortality

Nationally, opioid overdose mortalities are not evenly distributed, which can be seen in Figures 16–19 below (CDC, 2017). Figure 16 shows the U.S. spatial distribution by state of overdose mortalities due to all opioid drugs for the year 2017. The highest mortality rates were found in the northeastern states of Connecticut, Maine, New Hampshire, and Rhode Island and in Ohio and West Virginia. In general, the highest rates of mortality were found in the Northeast, Midwest, and upper Southeast The highest rate of mortality due to opioid overdoses was found in West Virginia at 43.9 deaths per

100,000. West Virginia is a rural state. However, many other rural states such as Montana, the Dakotas, and Wyoming had low rates. High rates in the Northeast and Ohio are most likely associated with heroin markets.

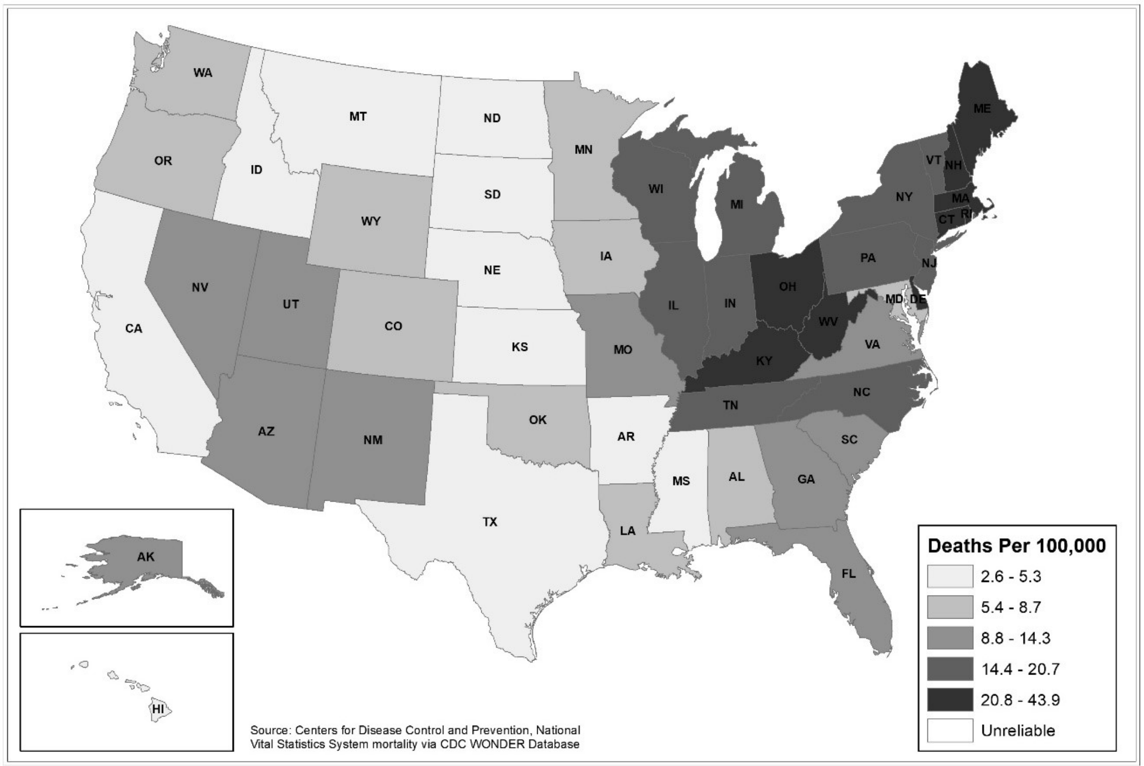

Figure 16. All Opioid Overdose Deaths Per 100,000 by State, 2017

The mortality rates from heroin and other synthetic narcotics by state are shown in Figures 17 and 18. Heroin overdose mortalities were concentrated in the midwestern states, northeastern states, and New Mexico. The highest rates were found in the District of Columbia and West Virginia at 17.9 and 13.3 deaths per 100,000, respectively. Synthetic opioid mortality rates were highest east of the Mississippi River in the midwestern and northeastern states. The highest rates were in West Virginia and Ohio at 33.3 and 29.5 deaths per 100,000, respectively. Most researchers believe that other synthetic narcotics' almost exclusive mortality rates east of the Mississippi are due to the difference in heroin drug markets (Mars et al., 2016). West of the Mississippi heroin is supplied from Mexican drug cartels in the form of black tar heroin, while the South American cartels that supply the drug market east of the Mississippi sell more-highly-processed powder heroin which is more easily adulterated with fentanyl (Mars et al., 2016, 2018). This aspect of the heroin markets has protected the western states from the fentanyl epidemic, but this may change with the reported rise in the use of fentanyl in areas around the Mexican border and as drug suppliers develop ways to adulterate black tar heroin with fentanyl (Debruyne, 2019; Sanger-Katz, 2018).

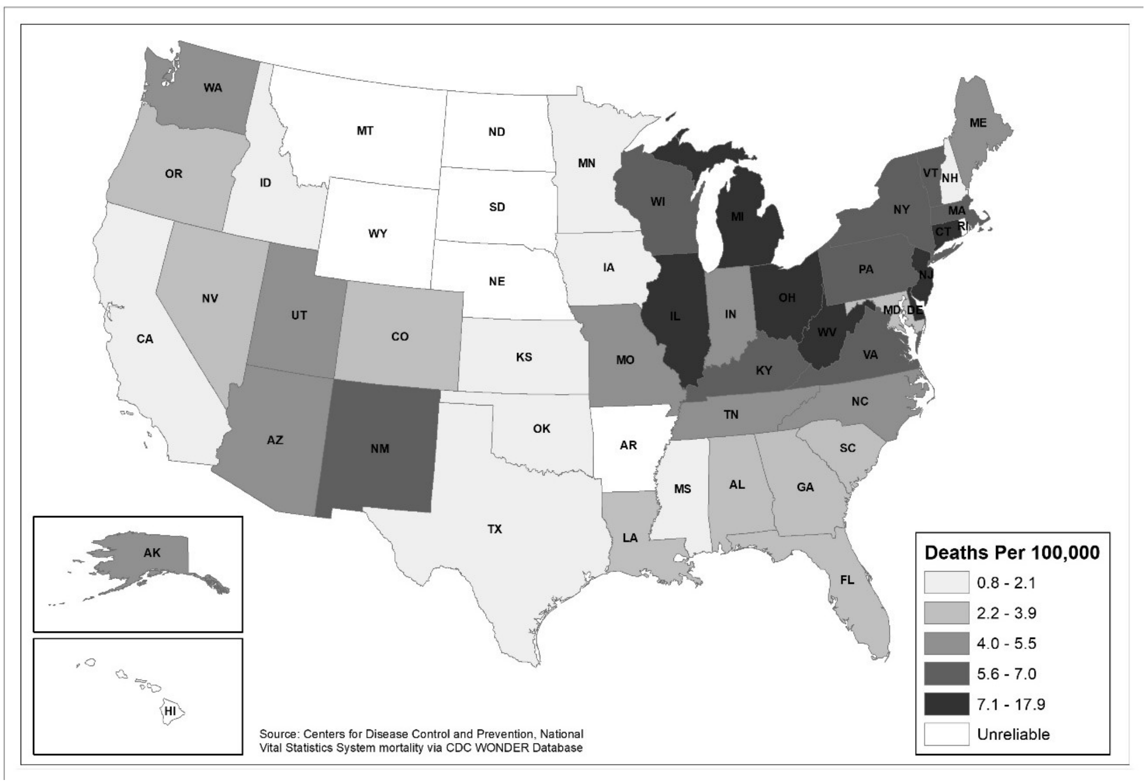

Figure 17. Heroin Overdose Deaths Per 100,000 by State, 2017

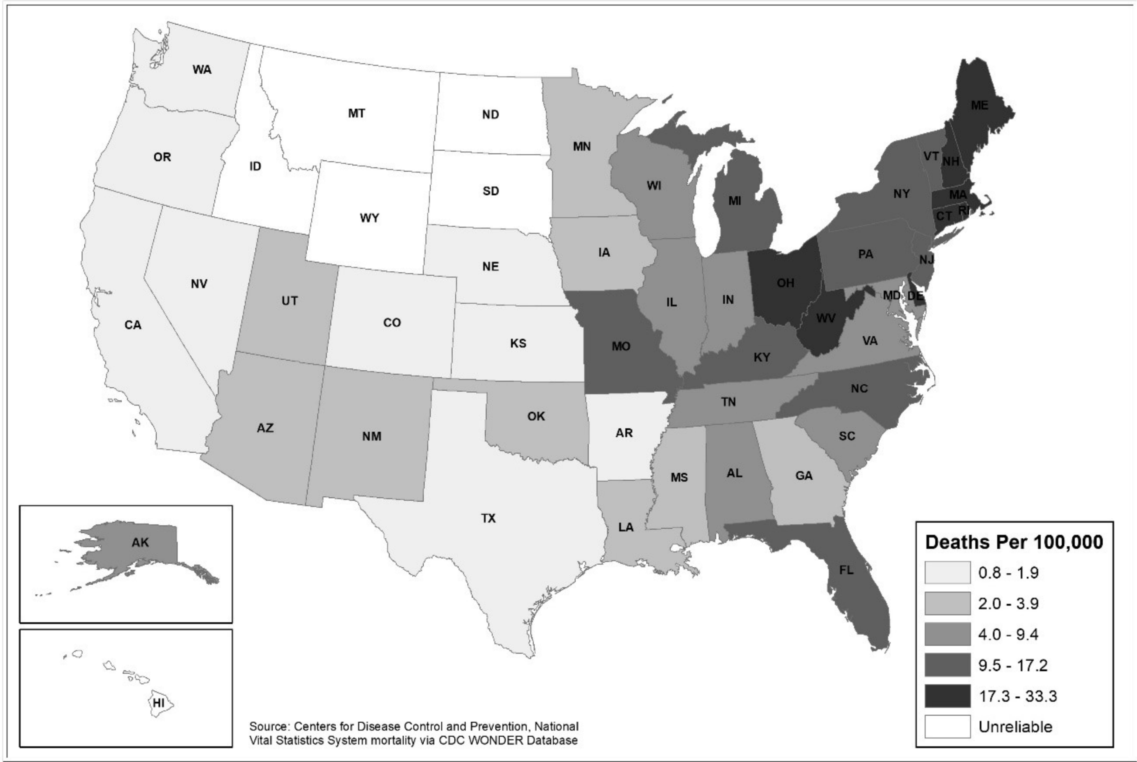

Figure 18. Other Synthetic Narcotic Overdose Deaths Per 100,000 by State, 2017

Mortalities associated with other opioids had high concentrations throughout the United States. Figure 19 shows the distribution of these mortalities. West Virginia had the highest rate of mortality at 14.3 deaths per 100,000. Other areas of high other opioid death rates were located in the Midwest, upper Southeast, Rhode Island, and Delaware on the eastern coast and in the western states of Nevada and Utah. The state of West Virginia had the highest rate of mortality for all the opioid classifications. This may be due to economic factors that affected the state. West Virginia had the second highest annual unemployment rate (5.2 percent) in the Continental United States behind New Mexico (5.9 percent), which also had high rates of heroin mortality (BLS, 2019).

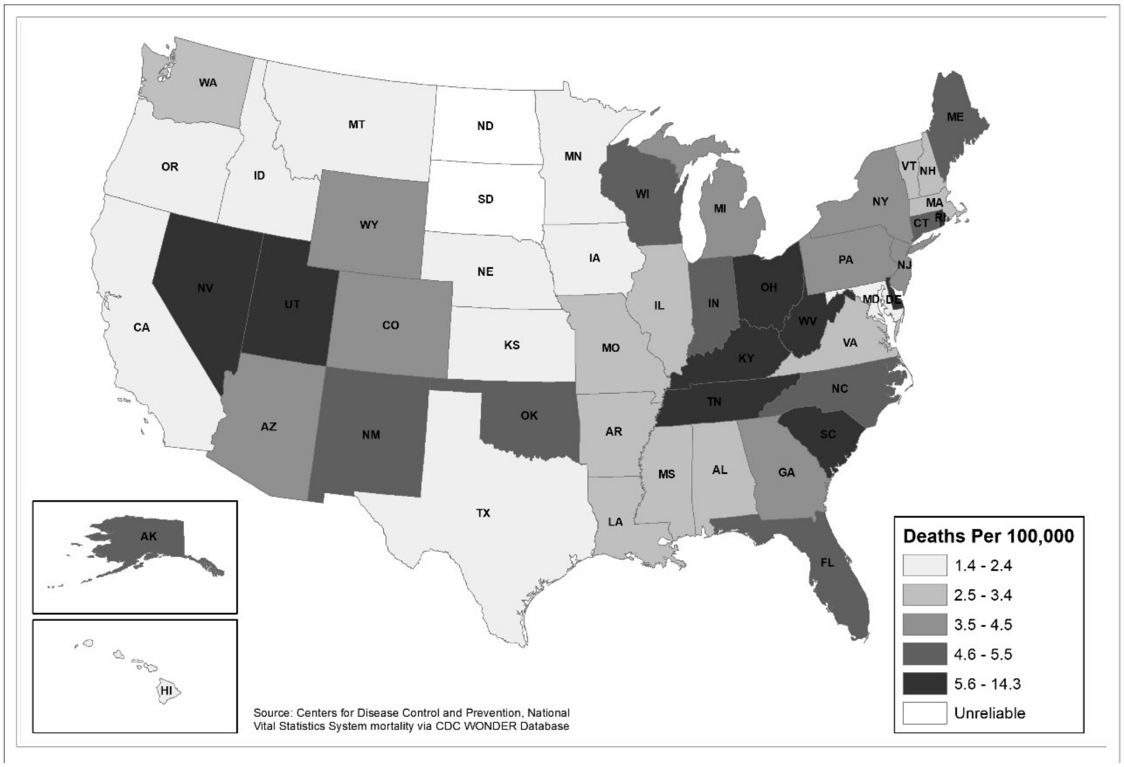

Figure 19. Other Opioid Overdose Deaths Per 100,000 by State, 2017

Utah is another state of interest. Utah ranked relatively high in other opioid mortalities compared to other states. This could be due in part to the state's large membership in the Church of Latter-day Saints. Previous research has shown a correlation between the faith and prescription opioid mortality in western states such as Utah, Idaho, and Wyoming relative to other western states which tend to have overdoses associated with other drugs (Kerry et al., 2016). Members of the church adhered to a stringent health code that prohibited the use of tobacco, alcohol, caffeine, and illicit drugs. It is hypothesized that prescription drugs are viewed as more acceptable for use and thus are more likely to be misused than are illicit drugs.

Male mortality rates were higher than those for females at the state level for all opioid drug classifications in 2017. The exception was for other opioids where females had higher rates than did males in Arkansas, Kansas, Minnesota, and Nevada.

The data were investigated at the county level to further explore the discrepancies between male and female mortality. Rate ratio maps for male-to-female mortality are presented in Figures 20–22. Data for the last decade, 2007–2017, were chosen for use unlike for previous maps which focused on data for 2017. This was done in order to account for small numbers of opioid-related deaths that occurred at the individual county level.

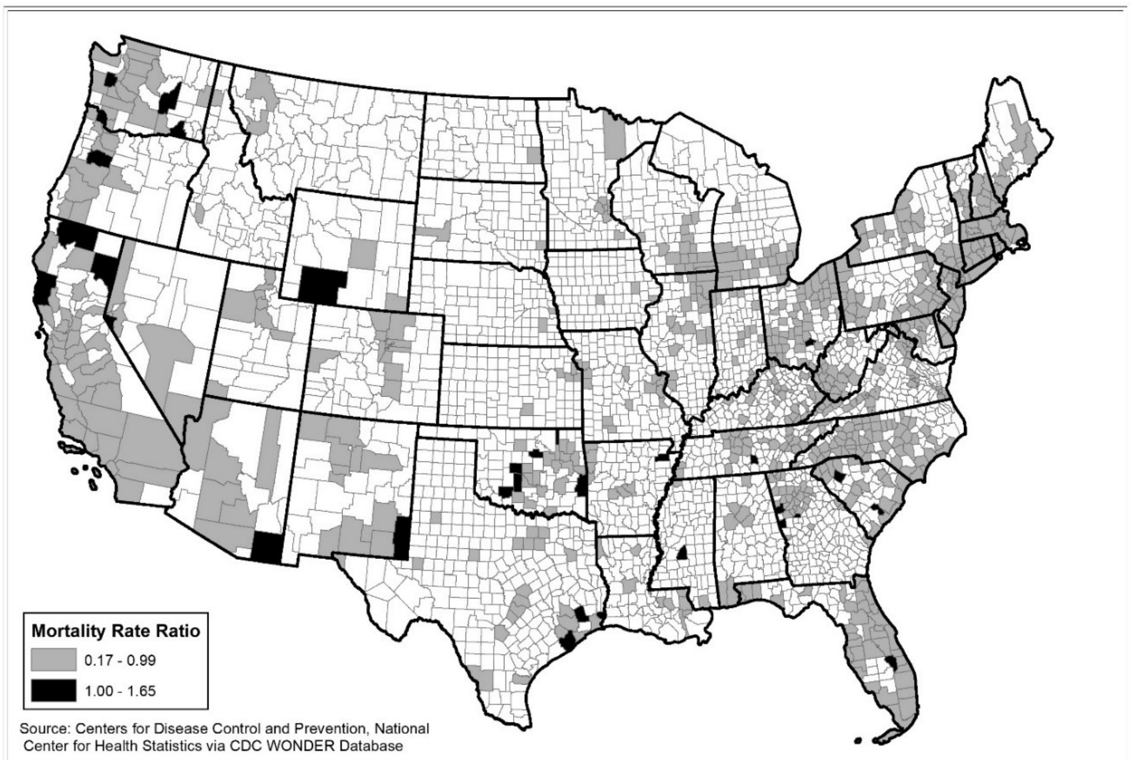

Figure 20. All Opioid Mortality Rate Ratio for Males to Females by County, 2007–2017

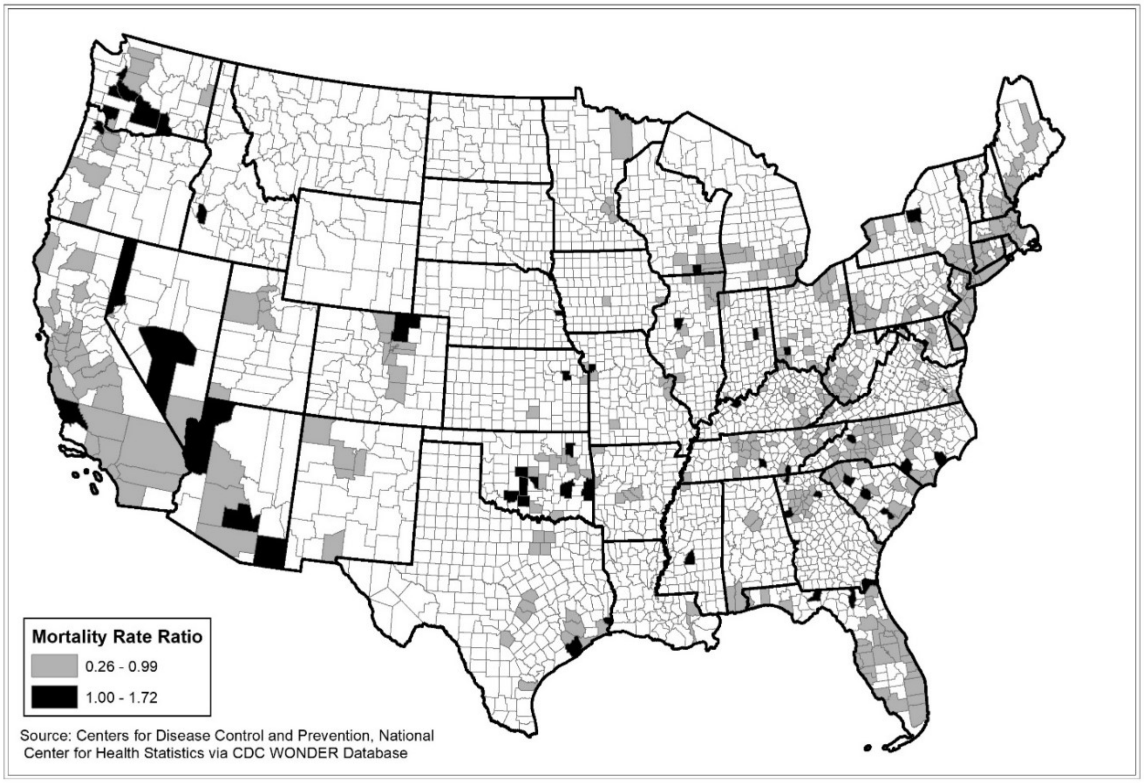

Figure 21. Other Opioid Mortality Rate Ratio for Males to Females by County, 2007–2017

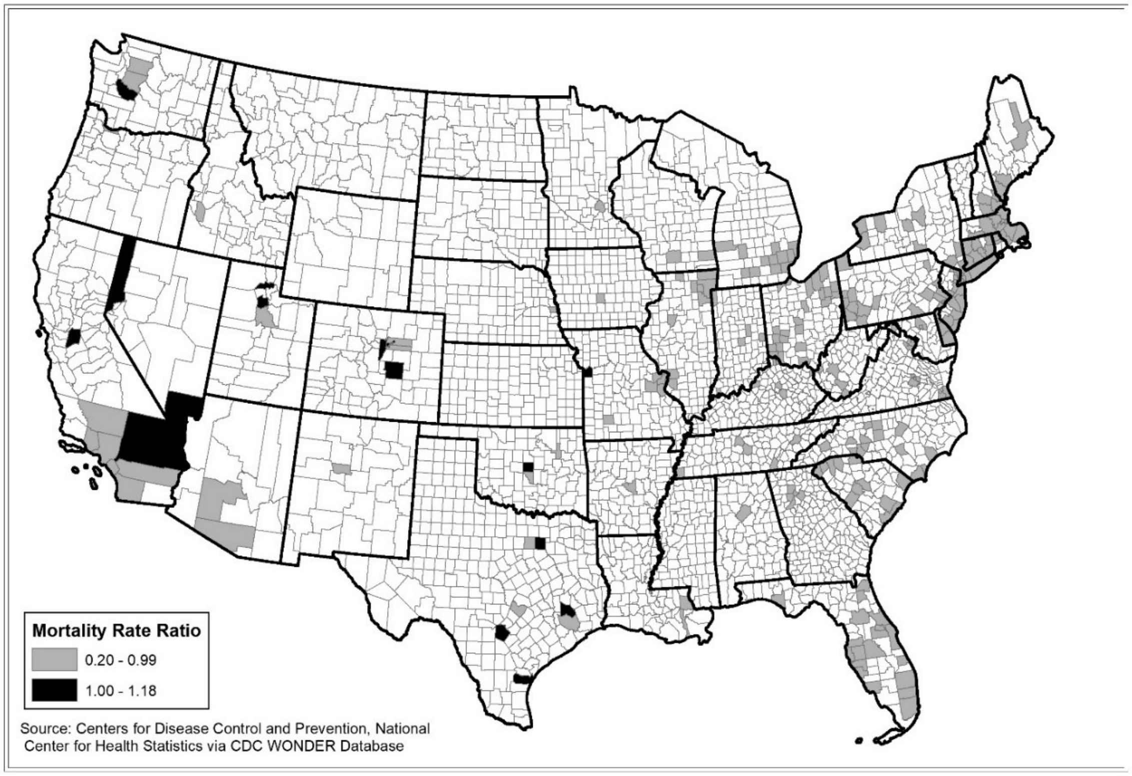

Figure 22. Other Synthetic Narcotic Mortality Rate Ratio for Males to Females by County, 2007–2017

Mortality rates for all opioids seem to be randomly scattered throughout the United States. However, most of the counties where female rates are higher are west of the Mississippi River, with pockets of concentration in the Southwest and the Pacific Coastal regions. A similar pattern is seen with other opioids, but with more dispersion. In Oklahoma, there is an interesting cluster of higher rates for females seen for both all opioids and other opioids.

During the time period considered, no counties had higher female rates of heroin mortality. However, most interesting is the pattern seen with other synthetic narcotics. While previous maps showed that synthetic opioids had had a greater impact east of the Mississippi River at the state level, there is a completely different pattern when looking at the differences between male and female mortality. All counties where women had higher levels of mortality were west of the Mississippi River. This may be due to lower levels of use in general in these areas.

Conclusions and Discussion

By analyzing the data from the CDC's NVSS-M database on opioid mortality, we found the notion that the opioid crisis had its largest impact on male, white, middle-aged, middle-class, rural, and suburban populations to be an oversimplification of the crisis. One point of this notion which is clear is that the crisis has had a larger impact in terms of male mortality. Males were more likely to die from opioid overdoses than were females. This may have less to do with opioids and more to do with males' overall drug use. According to the data in the CDC's NVSS-M database, it was found that males were more than twice as likely to die from an accidental drug overdose regardless of the drug.

However, this interpretation of the data as it relates to gender may be an oversimplification of the evolving epidemic. Recent research shows that women's heroin use is increasing at a faster rate than that of men, and women's rate of nonmedical use of prescription opioids is reducing more slowly than is males' (Becker & Mazure, 2019; Marsh et al., 2018). There are biological differences in how women experience pain, are more greatly affected by opioid drugs, and experience greater withdrawal symptoms (Marsh et al., 2018). In addition, there are non-biological differences such as women experiencing greater mental health issues (Marsh et al., 2018). Another factor that puts women at greater risk is the fact that they are prescribed opioids more frequently, as well as the complications of neonatal drug exposure (Marsh et al., 2018).

The notion that the crisis is associated solely with whites is also incorrect. The data show that African Americans, whites, and Native Americans were all impacted by the crisis. However, this misrepresentation of the epidemic being associated with whites may have been beneficial in influencing how policy-makers responded to the crisis. Previous drug epidemics such as the 1960s heroin and 1980s crack cocaine epidemics, which were widely considered associated with African Americans, resulted in the criminalization of drug use and policies such as the War on Drugs (Lopez, 2016). By contrast, policy-makers and health officials have responded to the current opioid crisis by treating it as a public health threat with strategies such as Narcan distribution, PDMPs, and promoting treatment as opposed to criminalization. This may not have been the case if the opioid crisis were considered an African American problem.

The idea that the crisis has been associated with rural populations may have resulted from the fact that West Virginia was one of the states hardest hit by the opioid epidemic. The state is rural and located in a part of the Appalachian mountain range that saw economic stagnation in the wake of the collapsing coal industry. The state has become a representation of the epidemic since it was one of the most impacted. However, this fails to describe the epidemic on a national level and in other regions of the United States. When we looked at the data, we found that heroin and fentanyl mortality had greater presences in urban communities, and prescription opioid mortalities were present in both urban and rural counties, debunking the notion of "hillbilly heroin."

The false demographic stereotype also fails to consider the historical development of the epidemic and its three waves. We are currently in the third wave, which is associated with increases in fentanyl mortality. Fentanyl's use is also evolving. Currently, the drug has been more prominent in eastern states due to differences in illicit drug markets. This is changing with increased fentanyl in Mexican drug supplies. Fentanyl is also being used in different ways by abusers as a safer, more reliable, and cheaper alternative to heroin (Szalavitz & Taylor, 2018).

Gender and race are important factors to consider when developing health interventions, treatment strategies, and public policy (Becker & Mazure, 2019). This is particularly important for an evolving public health threat such as the opioid crisis. Our findings suggest that there should be a critical gender-based approach to treatment and prevention. All data should be reported by gender so that researchers can provide gender-specific treatment and prevention strategies to practitioners and the public. Gender is also an important consideration when formulating drug prescribing practices and policies. A better understanding of the role of gender and race will lead to a more effective response to the current opioid crisis and future drug epidemics.

Chapter 3 A Review of Geodemographic Segmentation Systems and Spatial Data Analysis in Health Care Research

Introduction

The utilization of geodemographic segmentation (GS) in evidence-based health care creates new opportunities to identify unknown at-risk populations and to improve outreach, intervention, and disease prevention. The merger of health care data with GS systems into a spatial context enables the identification of relationships between clusters of health care disparities, disease, and population characteristics. GS allows researchers new ways to identify and describe populations in relation to their health and locations.

GS is traditionally a population classification tool used by marketing professionals. These systems leverage as many as hundreds of different data points associated with consumers such as demographics, purchasing patterns, credit reports, surveys, and other public and private records. The systems operate on the assumption that households with similar consumption patterns and socioeconomic characteristics cluster together. These clusters are linked to spatially defined segmentations that are associated with lifestyle characteristics such as preferred media consumption patterns, household spending, types of employment, preferred free time activities, and other generalizations about the populations living within.

Geodemographics analyze populations by where they live and suggest that where someone lives says something about who someone is (R. Harris et al., 2005). Geodemographics are based on the idea that individuals with similar characteristics cluster together and have comparable behaviors and preferences (Abbas et al., 2009; R. Harris et al., 2005). GS creates small area taxonomies that indicate the common socioeconomic status (SES) of the population that lives within the areas or neighborhoods (Abbas et al., 2009; Singleton & Longley, 2009; Singleton & Spielman, 2014). GS systems refer to the range of methods, classifications, datasets, and localities used to describe a population's similar SES, demographics, and lifestyles (Troy, 2008).

These systems are typically developed and maintained by private research firms. Examples are Experian's Mosaic, ESRI's Tapestry, CACI's Acorn, Nielsen Claritas' PRIZM, and Beacon Dodsworth's P^2 (*Acorn—The smarter consumer classification | CACI*, n.d.; *Claritas MyBestSegments*, 2017; *Esri—Tapestry*, n.d.; *Geodemographic Classification P2 People & Places*, 2017; *Mosaic USA Consumer Lifestyle Segmentation by Experian*, n.d.). Data from national censuses are often the basis for the segmentation classifications which are then built further upon using data from other sources such as surveys and credit card statements. GS systems attempt to develop a more complete representation of segmentations' and households' SES and lifestyle taxonomies than would be available using public census data alone. The segmentations are generally available at multiple geographic levels including state, county, postal code, census tract and block, household segmentation clusters, and individual household levels.

In addition to enabling the identification of potential consumers, GS systems also provide preferred channels of media communications through which to best reach target audiences. Not all populations share the same or preferred media consumption habits. Therefore, it is important to choose an appropriate channel through which to communicate with customers. GS identifies consumers and provides knowledge of which media channels to utilize to best reach them.

The following review of literature demonstrates how GS systems can be used in health care applications. It shows how these systems have been used previously to identify unknown at-risk populations and to improve outreach, intervention, and disease prevention.

Methods

A literature review was conducted to identify recent articles that examined the use of GS systems for the analysis of health care issues. Several online journal databases were queried which included: Public/Publisher Medline (PubMed), Google Scholar, and Journal Storage (JSTOR). The following keywords were used individually and in combination to search the databases: geodemographic segmentation systems, geodemographics, deprivation, health care, diabetes, smoking, obesity, BMI, social marketing, cancer, alcohol, GIS, Mosaic, ESRI Tapestry, Nielsen PRIZM, Acorn, and P^2. The searches sought to find health related papers published since 2000 that used GS systems as part of the research methodology or evaluated the use of GS systems for health care research.

The review discovered a limited amount of GS-related health care research, the bulk of which came from the United Kingdom. Singleton and Spielman hypothesized on this lack of previous research into GS and health care in the United States (Singleton & Spielman, 2014). While it is difficult to absolutely determine the reasoning, the authors suggest that this disparity is due to the availability of free geodemographics in the United Kingdom, either as academically-developed systems or freely-available commercial systems for academic use.

Twenty-three papers were found that met the review criteria. Table 4 presents the findings of the review.

Table 4. Summary of Studies of Geodemographic Segmentation Systems Used in Health Care

Citation	Analysis	Region/Date	Data	Condition
Geodemographic Segmentations as an Alternative to Measuring Deprivation				
Iyen-Omofoman et al., 2011	Used data to look for a correlation between lung cancer and segmentation data	United Kingdom/2000-2009	THIN, Mosaic, Townsend Deprivation Index	Lung Cancer
Sharma et al., 2010	Logistics Regression	United Kingdom/2008	The Health Improvement Network - incidents and survival, Mosaic, Townsend Deprivation Index	Smoking Prevalence
Douglas & Szatkowski, 2013	Logistics Regression	UK/July 2008-June 2010	460,938 Smokers' Records, Mosaic, Townsend Deprivation Index	Smoking Cessation
Nnoaham et al., 2010	Multilevel Logistic Regression	Southern England/2006-2008	Data on CRC screening uptake 88,891 individuals, IMD, P^2	Colorectal Cancer
Zhang et al., 2013	Linear Regression	UK/2001	P^2, UK Census, Index of Multiple Deprivation	Affluenza
Sheringham et al., 2009	Carr-Hill and Chalmers-Dixon reported test of criterion validity by correlating IMD against Acorn	England/April 2006-March 2007	Acorn, Index of Multiple Deprivation, National Chlamydia Screening Programme Data	Chlamydia

Table 4 (Continued)

Citation	Analysis	Region/Date	Data	Condition
Cheyne et al., 2013	Chi-square test, Kruskal-Wallis test, Mann-Whitney U test, Kaplan-Meijer survival analysis	Leeds, England/January 2008-December 2010	Acorn, Index of Multiple Deprivation, Lung cancer data from Leeds Teaching Hospitals	Lung Cancer
Geodemographic Segmentations for Measuring Deprivation				
Lin et al., 2015	Multilevel Survival Analysis	Texas/1995-2005	Texas Cancer Registry, Census, Mosaic	Cervical Cancer
Wiggans et al., 2015	Retrospective Analysis, Multivariate Analysis	UK/July 2005 - March 2012	Database of all patients with condition, Acorn	Colorectal Liver Metastasis
Wright & Polack, 2006	Stepwise Regression	England/1993-2004	Vaccine Coverage from District Health Authority and Primary Care Organization, 2001 Census, Mosaic	MMR Vaccine
Geodemographic Segmentations for Identifying Populations at Risk				
Farr & Evans, 2005	Predictive Analysis, matching cases to segments/descriptive analysis	Slough PCT, UK/2001-2002	UK NHS hospital episode statistics, Mosaic	Type 2 Diabetes
Powell et al., 2007	Predictive Secondary Data Analysis, involvement of primary care professionals	England, Slough Primary Care Trust/2001-2002	Mosaic, Hospital episode statistics	Type 2 Diabetes
Kimura et al., 2011	Pearson Chi-Square Test	Isahaya City, Japan/2004-2008	Isahaya City Medical Association Patient Data, Japan Census, Mosaic	Influenza A & B

Table 4 (Continued)

Citation	Analysis	Region/Date	Data	Condition
Amerson et al., 2014	Exploratory Analysis	Illinois, Selected Local Health Departments/2012-2014	Nielsen PRIZM	Smoking
Tomlinson et al., 2011	Crichton's Risk Triangle for risk analysis	Birmingham, England/2009	Mosaic, Census, MODIS	Urban Heatwave
Petersen et al., 2009	Found geodemographic data as a privately developed tool not appropriate for addressing public sector problem	London England, Borough of Southwark/2002-2005	Teenage contraception data and legal abortion data	Teen Pregnancy
Geodemographic Segmentations for Health Care Outreach				
Waqar et al., 2012	Retrospective analysis of nonattenders to screening	North East Devon England/April 2009-March 2010	Data from North East Devon Diabetic Screening Data, Mosaic	Diabetes Retinopathy Screening
Powell et al., 2007	Predictive, secondary data analysis	UK/2001-2002	Hospital Episode Statistics, Mosaic	Alcoholic Liver Disease
Moss et al., 2009	Proprietary data merger from Simmons Market Research	U.S./2004	Claritas PRIZM, BFRSS	Alcoholism

Table 4 (Continued)

Citation	Analysis	Region/Date	Data	Condition
Jennings et al., 2012	Pre and post intervention analysis using questionnaire, they looked at the p-value	UK/March - April 2009 & October-November 2010	Health Survey for England and National Hospital data, Mosaic	Chronic Conditions
Geodemographic Segmentation to Improve Spatial Analysis				
Grubesic et al., 2014	Evaluates the geodemographic correlates of Type 2 diabetes, county level research	US/2008-2010	Behavioral Risk Factor Surveillance System (CDC), County level data, ESRI Tapestry	Type 2 Diabetes
Drewnowski et al., 2014	Spatial Analysis and Regression Models	King County, Washington/2005-2006	Group Health Cooperative patient records, U.S. Census, CDC's Modified Retail Food Environment Index	Diabetes
Zhang et al., 2013	Multilevel Logistics Regression Model	U.S./2007	ESRI Tapestry Segmentation, ESRI Demographics, National Survey of Children's Health	Childhood Obesity

Results

All the reviewed articles demonstrate different use cases of GS systems in health care settings. They differed in the GS system used and the diseases in question. The papers also differed in whether their focus was to demonstrate GS systems as an alternative measure of socioeconomic deprivation, to identify populations with particular health risks, to recognize the use of the systems for health care outreach, or to improve spatial analysis.

Much of the literature, 10 papers, is used to evaluate the utility of GS for the measurement of deprivation as it relates to SES (Iyen-Omofoman et al., 2011; Sharma et al., 2010; Douglas & Szatkowski, 2013; Nnoaham et al., 2010; Sheringham et al., 2009; Cheyne et al., 2013; Xin Zhang et al., 2013; Lin et al., 2015; Wiggans et al., 2015; Wright & Polack, 2006). Deprivation is often a problematic concept to conceive, measure, and analyze (R. Harris et al., 2005; R. J. Harris & Longley, 2002; C. Jones et al., 2005). This can be attributed to the uncertainty of the meaning of deprivation and heterogeneity within and among geographic locations (R. J. Harris & Longley, 2002; C. Jones et al., 2005).

Socioeconomic deprivation is often viewed differently among nations or regions within a nation. In some areas, lack of food and shelter would be an indication of socioeconomic hardship, while in others ownership of an automobile could serve as a standard measure. Therefore, determining the best datum or set of data to represent the presence of deprivation can be difficult (R. J. Harris & Longley, 2002).

Much of the data used to measure deprivation is collected by government and public entities such as censuses with multiple intended purposes. In the U.S., programs such as the U.S. Census and the American Community Survey (ACS) are frequently used as measures. In the UK, indices using public data have been created to measure deprivation such as the Townsend Deprivation Index, Jarman Underprivileged Areas Index, the Carstairs Index, Breadline Britain, and the Index of Multiple Deprivation (C. Jones et al., 2005; Locker, 2000).

GS systems have been proved as an alternative to using public data or indices for measuring deprivation of SES among populations. The data are typically more up to date and are collected at small levels of granularity, including down to the household level. The GS systems, which are built upon public data such as censuses, are further enhanced with additional data sources and frequent surveys to overcome the limitations of using public data sources alone. Additionally, GS uses a multivariate approach that limits problems associated with margins of error of univariate data collected at small-scale levels such as with the ACS (Spielman & Singleton, 2015). Segmentation data are frequently used by the private sector in the U.S. and Europe to supplement and sometimes replace small-area data collected by censuses to overcome their weaknesses (R. Harris et al., 2005; R. J. Harris & Longley, 2002; C. Jones et al., 2005; Locker, 2000).

Geodemographic Segmentations as an Alternative to Measuring Deprivation

Seven of the reviewed papers attempt to evaluate various GS systems with two established measures of deprivation in the United Kingdom and England, the Townsend Deprivation Index and the Index of Multiple Deprivation (IMD) (Cheyne et al., 2013; Douglas & Szatkowski, 2013; Iyen-Omofoman et al., 2011; Nnoaham et al., 2010; Sharma et al., 2010; Sheringham et al., 2009; Xin Zhang et al., 2013). The Townsend Deprivation Index, first established in 1988, is an area-based measure of deprivation used throughout the United Kingdom based on four areas of Census data: households without cars, overcrowded households, households not owner-occupied, and persons unemployed. The scores for the four areas are weighted together to calculate the Townsend Deprivation Index score for the Census geographies of wards, enumerated districts, and output areas (Martin, 2007).

Three of the papers from the review compared the use of Experian Mosaic to the Townsend Deprivation Index for quantifying deprivation (Douglas & Szatkowski, 2013; Iyen-Omofoman et al., 2011; Sharma et al., 2010). The first of these papers used data collected in the United Kingdom from The Health Improvement Network (THIN), a database of patient information from primary care providers to analyze incidents of lung cancer diagnosis and survival between 2000 and 2009 (Iyen-Omofoman et al., 2011). The authors were looking to compare the use of the Townsend Deprivation Index quintiles with Experian's Mosaic GS in the correlation between lung cancer incidents and socioeconomic deprivation. While they found a link between increased socioeconomic deprivation in both systems, there were wider variations in the incidents of lung cancer among Mosaic's geodemographic groupings. The authors concluded that since the Mosaic GS was derived from a broader selection of variables, it provided a deeper understanding of the population and various geodemographic types, unlike the Townsend Deprivation Index which was limited to Census data on deprivation at the postal code level.

A second paper also compared the use of the Townsend Deprivation Index to Experian Mosaic GS but considered the association between smoking and socioeconomic deprivation (Iyen-Omofoman et al., 2011; Sharma et al., 2010). This differed from the previous paper by looking at the cause as opposed to the disease outcome to deprivation. The cross-sectional study also used data from the THIN general practitioners' patient database from January 2008. The authors of this study found that smoking prevalence increased with a rise in deprivation using both the Townsend Deprivation Index of Multiple Deprivation and Mosaic GS. However, the ranges of smoking prevalence were found to be greater across the 11 Mosaic groupings and 61 Mosaic types of geodemographics than across the Townsend Deprivation Index quintiles. The authors suggested this greater variation gives a better understanding of the prevalence of smoking among the population.

A follow-up paper built upon Sharma et al.'s work considered the relationship between deprivation and smoking cessation (Douglas & Szatkowski, 2013; Sharma et al., 2010). This was a slightly different take on the topic by looking at the association between intervention and deprivation. Like the previous studies, it used the THIN general practitioners' patient database and again sought to compare the Townsend Deprivation Index to Mosaic GS. The data they used for the study were selected from July 2008-June 2010. They found that people with lower socioeconomic status and with higher levels of deprivation were less likely to receive information about how to quit smoking and less likely to receive medication to help them quit. All three of these studies found that Experian's Mosaic GS system was a useful tool for identifying varying levels of socioeconomic deprivation and various aspects of lung disease compared to the Townsend Deprivation Index, which iss based on public data.

Unlike the Townsend Deprivation Index, which is based on several British Census geographies, the IMD measures deprivation using Census data for the English Census geographies known as Lower-layer Super Output Areas (LSOAs) of which there are 32,844 in the 2015 vintage of the measure. LSOAs have an average of 1,500 residents and are the small area of the Census data or neighborhood level. There are seven categories of Census data used to calculate the IMD in the 2015 measure: income, employment, health deprivation and disability, education skills and training, barriers to household services crime, and living environment. Once the IMD is calculated for each LSOA, LSOAs are ranked in order to compare LSOAs in their level of deprivation from lowest to highest (*Index of Multiple Deprivation—Facts and Figures*, n.d.; *The English Index of Multiple Deprivation (IMD) 2015 Guidance*, 2015).

Four of the articles compared the use of the IMD to GS systems (Cheyne et al., 2013; Nnoaham et al., 2010; Sheringham et al., 2009; Xin Zhang et al., 2013). The first paper presented the findings of an analysis that used the P^2 geodemographic typologies to assess the uptake of colorectal cancer (CRC) screenings in Southern England (Nnoaham et al., 2010). The authors used a multilevel regression model to analyze data from the National Bowel Cancer Screening Programme for the years 2006–2008. The analysis was presented as an alternative to composite indices of area deprivation such as the IMD. The P^2 GS is a commercially-available system by Beacon Dodsworth freely available to National Health Service researchers. It was found that the GS gives them a better understanding of population behavior in its context due to its use of a more diverse set of variables and its focus on marketing to particular groups. CRC screening linked to data from the England Census' LSOAs using postal codes. The P^2 GS system was found to be better at explaining variations in the population's uptake in CRC screenings than was the IMD. The authors found that the GS typologies associated with low uptake had characteristics of single pensioner households renting council housing or housing associated properties that had a high degree of ethnic mix.

An additional paper reviewed the use of P^2 in comparison to the IMD (Xin Zhang et al., 2013). The research discussed the difficulty of measuring deprivation using IMD. To address this, the methodology divided LSOAs with P^2 GSs to achieve greater geographic granularity. They used these P^2 new geographies and compared them to data from the 2001 UK Census pertaining to Limiting Long-Term Illness and individuals' self-reporting of "not good health." The study sought to better understand the relationship between inequity and health by analyzing the spatial relationships of deprivation. The researchers found that areas geographically adjacent to areas of greater affluence or low deprivation had high levels of self-reported morbidity to the UK Census survey.

Acorn is another GS system that is available in the UK. The Acorn system was compared to the IMD for use to improve monitoring by the National Chlamydia Screening Programme (NCSP) in England using data from April 2006–March 2007 (Sheringham et al., 2009). The NCSP did not collect socioeconomic data, and the IMD was used as a proxy. The paper noted that the NCSP had reasons to suspect that young people were more vulnerable to poor sexual health due to the high mobility and the greater tendency to live in communal settings such as dorms and army barracks. It was hypothesized that Acorn in conjunction with the IMD could provide additional insight into addressing issues of sexual health inequalities as opposed to using the IMD alone. There were two reasons for the hypothesis. Acorn has a greater geographic granularity, which reports data at the postal code level, than does the IMD, which is based on LSOA. Acorn also has a separate categorization for people living in communal environments.

The study used Carr-Hill and Chalmers-Dixon criterion validity testing to compare the results of using IMD and Acorn to identify populations with sexual health deprivation. The analysis found that Acorn and IMD agreed moderately well when identifying the socioeconomics of the populations tested. However, Acorn added value in two ways. There was value in the greater granularity of Acorn. This enabled the ability to show postal codes where screening coverage and deprivation were highest within LSOAs. They were also able to identify the areas where people were most likely to reside in communal living. This showed spikes in screening in these neighborhoods, but the authors cautioned that this may just be due to higher concentrations of individuals. The paper concluded that further research should be done into geographic areas in which IMD and Acorn did not show agreement on socioeconomics. It was also pointed out that measures taken at postal codes are still area level and cautioned that there will be population heterogeneity.

A final study using Acorn and IMD, which looked at GS systems as an alternative method for measuring deprivation, found conflicting results with the previous papers in this review (Cheyne et al., 2013). The paper, which studied cancer stage at presentation and disease outcome, did not find a positive correlation between socioeconomic deprivation and disease (Douglas & Szatkowski, 2013; Iyen-Omofoman et al., 2011; Nnoaham et al., 2010; Sharma et al., 2010; Sheringham et al., 2009). The research took place in England using data from a single hospital, the Leeds Teaching Hospital NHS, from 2008–2010. It was hypothesized that lower socioeconomic status would have a negative effect on lung cancer outcomes due to attitudes of cancer fatalism and that these patients would have greater delays in seeking help for treatment because of a lack of awareness of cancer warning signs. The patient records were matched to the IMD quintiles and the Acorn segmentations then run through several statistical models. The analysis found no interaction between the stage of lung cancer diagnosis or outcomes and socioeconomics. These findings matched a study relating to deprivation and disease conducted in Scotland during the 1990s but conflicted with a similar, more recent study from Texas (Brewster et al., 2001; Philips et al., 2011). It was concluded that uniformity across socioeconomic classes was due to the United Kingdom's National Health Services, which offers free universal health care access to all socioeconomic groups, which differs from health care in the United States.

All the papers showed how GS systems could improve upon or add to other previously established indexes or measures of deprivation. Several common themes found in these papers were improvements due to wider ranges of variables used to create GS systems, improved geographic granularity, additional measures, and improving on explaining variations. The final paper did not find a positive correlation between socioeconomic deprivation and disease. The next section explores GS as a measure of deprivation.

Geodemographic Segmentations for Measuring Deprivation

Several other papers reviewed used GS systems to measure deprivation but did not compare them to previously developed indices of deprivation (Lin et al., 2015; Wiggans et al., 2015; Wright & Polack, 2006). All these papers also found somewhat unsuspected correlations between deprivation and disease. The first paper examined the association between women's socioeconomic disparity and cervical cancer survival using socioeconomic data from Mosaic (Lin et al., 2015). The study took place in Texas using data of cancer records from the Texas Cancer Registry for 1995–2005. The study controlled for a number of socioeconomic factors using data from the U.S. Census and data from a private firm, which provided health insurance expenditure and behavioral data from Experian. They also controlled for the types of tumors and treatments received as well as other individual variables. The research used multilevel survival analysis to determine the correlation between five-year cervical cancer specific mortality and socioeconomic factors such as race. The study found that African American women had a higher mortality risk (HR 1.19; 95% CI, 1.03-1.38) than did other races, while Hispanics had a survival advantage over non-Hispanics whites when all other factors were controlled for (HR 0.80; 95% CI, 0.69-0.94). This was puzzling since Hispanics had higher levels of socioeconomic deprivation than did non-Hispanic whites. Several explanations for this “Hispanic Paradox” included selective return migration from the U.S. toward the end of life (this could also contribute to a loss at follow up), comorbid conditions, social networking, religion, smoking status, and cultural factors.

Another paper considered the association between socioeconomic status and whether patients received liver resection treatment for colorectal liver metastasis (CLM) (Wiggans et al., 2015). A database was obtained of all patients who underwent a liver resection for CLM in the United Kingdom between July 2005 and March 2012. The patient records were matched to one of five geodemographic typologies from the Acorn GS system which ranged from least to most socioeconomically deprived. The research findings showed that although incidents of primary colorectal cancer were associated with higher levels of economic deprivation, geodemographic groups with lower levels of deprivation were more likely to receive liver resection treatment for CLM. It was hypothesized that this is due to the economic and social barriers that must be overcome between primary treatment and becoming a candidate for liver resection surgery. It was also found that there was no significance between the long-term survival rates of liver resection for CLM and socioeconomic deprivation.

A final paper found similar findings of a negative correlation between deprivation and disease in regard to Measles-Mumps-Rubella vaccination uptake in England (Wright & Polack, 2006). Using Mosaic, vaccine coverage data, and the British Census, it was found that populations of higher socioeconomic status had higher declines in vaccine coverage between 1993 and 2008. Inner-city areas with high levels of deprivation had the lowest rates of decline in vaccine uptake during the same period.

The papers in the previous two sections demonstrated the use of GS as a way to measure socioeconomic deprivation and how that deprivation correlates to disease. The papers of the next section take a different approach by identifying at-risk populations using GS.

Geodemographic Segmentations for Identifying Populations At Risk

One of the potential applications of using GS to analyze health care data is to identify unknown at-risk populations to improve outreach, intervention, and prevention. Early screening and referral of at-risk populations can have a significant impact on mortality and morbidity. Diseases such as Type 2 diabetes can have long periods of latency. It is estimated that patients can go 9 to 12 years without being diagnosed. Early screening, referral, and diagnoses of Type 2 diabetes can limit the impact of complications such as blindness, kidney failure, and nerve damage (Farr & Evans, 2005; Lanza et al., 2007).

Additionally, diseases such as lung cancer are often not diagnosed until curative treatment can no longer be offered to patients, and there is often an inequality between SES and screening (Iyen-Omofoman et al., 2011). Not only can GS improve patients' morbidity and the financial burden of disease, but it also can lower cost to the public health systems (Sharma et al., 2010). Six of the papers reviewed focused on identifying populations at risk (Farr & Evans, 2005; Powell, Tapp, Orme et al., 2007; Amerson, 2014; Kimura et al., 2011; Tomlinson et al., 2011; Petersen et al., 2009).

One study described a pilot project that used GS and social marketing to identify unknown cases of Type 2 diabetes in the town of Slough in the United Kingdom (Farr & Evans, 2005). The study used data of Type 2 diabetes cases from the United Kingdom's National Health Services Hospital Episode Statistics from 2001–2002 and overlaid it on Experian Mosaic geodemographic classification data at the postal code level. The methodology revealed seven GSs that had a predisposition to higher rates of Type 2 diabetes. The GSs associated with Southeast Asians were of particular interest, and a targeted social marketing campaign was developed to promote screening and referral. In 2005, the results of the pilot study showed a 164.0 percent increase in diabetes referrals in the Slough area.

Another study built upon the work of Farr & Evans by illustrating an approach by which primary-care professionals can be included in outreach to individuals with a high risk of developing Type 2 diabetes (Farr & Evans, 2005; Powell, Tapp, Orme et al., 2007). This study also took place in the area of Slough, England, and used the Hospital Episode Statistics from 2001–2002 of Type 2 diabetes diagnoses and data from the Mosaic GS system. Geodemographic profiles of individuals who were most likely to be susceptible to Type 2 diabetes were generated using predictive secondary analysis. These profiles were associated with higher levels of socioeconomic deprivation such as low incomes and education levels. The methodology also found a high association between older age and Type 2 diabetes, and like the previous study, they found an association between the disease and Asian populations.

Another paper, which focused on identifying at-risk Asian populations, reported the link between age and the incidents of influenza A and B in Isahaya City, Japan, between 2004 and 2008 (Kimura et al., 2011). The study used data collected by the Isahaya City Medical Association on patients diagnosed with influenza and appended it to Mosaic GSs for Japan. The results of their analysis showed that segmentations associated with young couples that had young children had a 10.0 to 40.0 percent greater rate of influenza than the calculated expected average index rate. Segmentations associated with older populations living in rural areas had a 20.0 to 50.0 percent lower rate.

Another paper demonstrated how geodemographic data can be used to identify at-risk populations of smokers (Amerson, 2014). The project took place in 94 selected Illinois local health departments between 2012 and 2014. The authors noted that traditional health data such as the Behavioral Risk Factor Surveillance System (BRFSS) only provides information at the county level and that the health departments needed greater geographic granularity to conduct more efficient public information campaigns and reach smokers with information about smoking cessation. Nielsen’s PRIZM was used to create custom community profiles for each of the health departments’ counties. These profiles revealed the PRIZM segmentations which were highly associated with smokers.

These segmentations were mapped at the Census tract and ZIP code levels to identify communities with high smoking rates.

One paper used a more novel dataset compared to the others. Mosaic GS was used along with British Census data and the NASA remote sensing data MODIS to show the connection between urbanicity, socioeconomic status, old age, and vulnerability to heatwaves in Birmingham, England (Tomlinson et al., 2011). The study concluded that urban residents are more susceptible to higher temperatures and in particular Mosaic household types that are associated with old age.

Not all the researchers were proponents of GS systems for identifying populations at risk. One paper presented a number of new methods for addressing individuals at high risk for teenage pregnancy (Petersen et al., 2009). The study took place in the London Borough of Southward, which had one of the highest teenage pregnancy rates in England. Data from teenage contraception dispersal and legal abortions between 2002 and 2005 were used for the review. The authors favored risk estimates and risk mapping to identify areas of high risk. It was recommended that identifying at-risk areas should be followed by working with secondary schools and general practitioner practices in the areas. They opposed the use of geodemographic data. They argued that although GS provides greater granularity for research, it is inappropriate to use private data to properly address a public health issue.

While beneficial, identifying the at-risk population is not enough (Powell, Tapp, Orme et al., 2007). Two of the papers demonstrated how GS systems could be used to conduct outreach after a population is identified (Amerson, 2014; Powell, Tapp, Orme, et al., 2007). In one paper, the authors called for a targeted marketing campaign with direct mailings and telephone canvassing, and that health care providers should be included as a communication channel through which populations of individuals at risk of developing Type 2 diabetes could be reached with information about prevention (Powell, Tapp, Orme et al., 2007). Another paper discussed how Nielsen ConsumerPoint, a software used for target marketing, was used to determine shopping and lifestyle preferences as well as media consumption patterns (Amerson, 2014). This information was used to create targeted health campaigns to promote smoking cessation. The next section carries on with this theme by showing additional ways GS systems can be used for health care outreach.

Geodemographic Segmentations for Health Care Outreach

Geodemographic segmentation systems are not limited to identifying populations at risk of disease. They can also be used in conjunction with social marketing to address health care inequalities through awareness campaigns. Social marketing differs from commercial marketing in that the goals of such efforts are to promote behavioral changes in the population that will result in improved health (Farr et al., 2008; Lanza et al., 2007). Geodemographic systems provided by private companies will include the necessary information on appropriate channels through which to reach the desired population segmentations. This can allow for more efficient, more targeted, and more cost-effective health care (Lanza et al., 2007). Four papers from the review had outreach as a primary focus (Jennings et al., 2012; Moss et al., 2009; Powell, Tapp, & Sparks, 2007; Waqar et al., 2012).

One of the papers analyzed the association between nonattenders to diabetic retinopathy screening and socioeconomic status using GS (Waqar et al., 2012). The study reviewed data collected between April 2009 and March 2010 by the North and East Devon Diabetic Retinal Screening Service in England. Patients were sent reminders in the mail to schedule a series of screenings. Screening attendance data were matched to Experian Mosaic geodemographic classifications using postal codes. It was found that successful professionals and active retired communities had the lowest rates of non-attendance, while areas with social housing had the highest rates of non-attendance. The authors of the paper argued that this shows an association between socioeconomic deprivation and non-attendance. However, the reasons were unclear. They suggested more focused and customized strategies were needed to target non-attenders.

Two papers looked at the use of GS systems to reach heavy drinkers (Moss et al., 2009; Powell, Tapp, & Sparks, 2007) The first paper used GS to draw a connection between heavy episodic drinking that can lead to liver disease and lower socioeconomic status (Powell, Tapp, & Sparks, 2007). The study took place in England and appended data from the Hospital Episode Statistics, 2001–2002, dataset to Mosaic lifestyle segmentations at the post-code level. The research found an association between deprived geodemographic types and heavy drinking patterns. The authors argued that this information can be used to better understand people of lower socioeconomic status and thus create more targeted media campaigns to curb heavy drinking and create policies that promote healthier lifestyles. The second paper demonstrated how geodemographic data can be used to cost-effectively identify segments of heavy drinkers using 2004 BFRSS data and Claritas' PRIZM (Moss et al., 2009). The study used a proprietary algorithm obtained from a private research firm to identify clusters of heavy drinkers. Staff from the National Institutes on Alcohol Abuse and Alcoholism selected five clusters for further outreach, prioritizing those that were associated with youth, that comprised the highest percentage level of alcohol abusers, and that were most likely to benefit from media intervention. The researchers determined that the clusters associated with youth were the most likely to use online media, and this was the most efficient way to reach them.

The final paper looking at outreach presented a case study that used GS to plan the routes of Mobile Food Stores (MFS) providing discounted produce in the United Kingdom (Jennings et al., 2012). The goal of the targeted intervention was to increase the intake of fruits and vegetables to the recommended five servings per day. Researchers determined the at-risk populations using findings from the Health Survey for England and National Hospital data. Experian Mosaic Public Sector Software was used to plan the routes for the MFSs that would reach the at-risk populations. Pre- and post-intervention surveys were conducted to evaluate the effectiveness of the intervention. It was found that there was a 25.0 percent increase in the number of participants consuming five servings of produce per day and that 85.0 percent of participants consuming less than one serving per day were now consuming one or more servings.

Geodemographic Segmentation to Improve Spatial Analysis

The final section of the literature review demonstrates how GS can be used to improve spatial analysis. Three of the papers reviewed focused on geographic considerations and methods when using data from GS systems (Drewnowski et al., 2014; Grubesic et al., 2014; Xingyou Zhang et al., 2013). The first study focused on spatial clustering by GS taxonomy and used ESRI Tapestry GS systems in the exploratory analysis of county level Type 2 diabetes rates (Grubesic et al., 2014). The data for the study came from the BFRSS survey for the years 2008–2010. The purpose of the research was to challenge the idea of the "diabetes belt" cluster found in the U.S. Southeast. The methodology used a Moran's I statistical analysis to identify clusters of counties associated with high and low rates of Type 2 diabetes incidents and like geodemographic types. The clusters from their analysis differed from the belt pattern and identified hot spots within the Southeast. The research concluded that the geodemographic classifications are based on hundreds of variables that relate to lifestyle as opposed to limited variables such as age, race, or ethnicity. The classifications offered a more comprehensive view of the lifestyles associated with Type 2 diabetes.

Two papers presented GS systems as an alternative to using government data due to its limited small area geographic scale and frequency of collection (Drewnowski et al., 2014; Xingyou Zhang et al., 2013). Government data are often collected at administrative, ad hoc, or regional boundaries intended for multiple purposes. Therefore, there is no guarantee that these boundaries will effectively coincide with areas of deprivation or disease. Additionally, the geographies can be too coarse in their granularity, creating heterogeneity among the population in relation to its deprivation. This causes ecological fallacy in which the measure of the population for an area does not adequately represent all the individuals therein (Grubesic et al., 2014; Robinson, 1950). Moreover, public data are often infrequently collected. Examples of this are the U.S. and UK censuses which are conducted every 10 years. These are supplemented with survey data, often with unacceptable margins of error for the small area levels of analysis used in health research (R. J. Harris & Longley, 2002; C. Jones et al., 2005; Locker, 2000). In some health care applications, data must be obtained with small-area estimates of SES.

An example of this would be a local health agency with scarce resources that only can afford to target areas with the greatest need (Drewnowski et al., 2014).

The first study demonstrated some of the difficulty and limitations of using public data for small-area spatial analysis. The paper looked at the correlation between SES and diabetes in a large sample of insured adults in Kings County, Washington, between 2005 and 2006 (Drewnowski et al., 2014). The research used patient records of diabetes diagnosis from the Group Health Cooperative, and socioeconomic variables came from the U.S. Census. A second group of SES variables considering food quality/availability came from the CDC's Modified Retail Food Environment Index. The diabetes diagnoses were geocoded to Census tract data which served as the small area geographies for the study. Importantly, the authors noted that most research of disease comes in the form of state or county level which can be insufficient for health care research. The findings of the spatial regression model revealed that home value and college education were more strongly correlated with diabetes than was household income. The reported level of diabetes incidents for King County from the BFRSS from 2006–2010 was 6.0 percent. The range of incidents at the Census tract level within King County from the study was from 6.9 to 21.2 percent, with a non-normalized geographic distribution of the highest concentrations in the south and southwest portions of the county. This illustrates the benefit of subcounty, small area studies for the design of community-based outreach, prevention, and control and the limitations of the BFRSS, which reports data at the county level.

The second paper demonstrated the utilization of ESRI's Tapestry Segmentation data as a control for lifestyle and socioeconomic status in a multilevel logistics regression model analyzing childhood obesity (Xingyou Zhang et al., 2013). The research sought to explain the condition in the United States with small-area estimates, such as block-group levels, using county and ZIP code level data from the 2007 National Survey of Children's Health and demographic data also from ESRI. The model was able to significantly account for levels of childhood obesity at the small-area level and gave researchers the ability to demonstrate the importance of location in its relation to childhood obesity.

Conclusions

This review revealed that there has been a limited amount of academic research into GS systems and their implementation into health care research. The research that has been done can be put into five general categories: GS as an alternative to established measures of deprivation, using GS to measure deprivation, using GS to identify populations at risk of certain diseases, GS as a component of health care outreach, and using GS to improve spatial analysis. The previous research, while limiting, demonstrated how GS systems can be used within the framework of evidence-based health care to improve the identification of unknown at-risk populations and to improve outreach, intervention, and prevention.

The review showed the ways that GS systems offered an important alternative to using traditional methods of measuring deprivation with data such as censuses and indexes created from public data. Using public-sector data can create challenges when used to measure deprivation of SES. GS systems address some of these issues by offering data that are collected more frequently at multiple geographic levels. Increased spatial granularity and temporal frequency of collection can improve health research (Amerson, 2014; Douglas & Szatkowski, 2013; Iyen-Omofoman et al., 2011; Sharma et al., 2010).

Three of the papers demonstrated how Experian Mosaic performed better at measuring deprivations than the Townsend Deprivation Index (Douglas & Szatkowski, 2013; Iyen-Omofoman et al., 2011; Sharma et al., 2010).

Several papers demonstrated that GS systems could be used as a tool for defining SES and deprivation (Lin et al., 2015; Wiggans et al., 2015; Wright & Polack, 2006). The papers verified that GS systems could be used to categorize SES. However, all found some example of an inverse correlation between the expected relationships between SES and disease.

The review also demonstrated how GS can be used to identify populations at risk. Two papers demonstrated how Experian Mosaic could be used for the early identification of Type 2 diabetes (Farr & Evans, 2005; Powell, Tapp, Orme et al., 2007). The authors were able to use GS to identify a connection between low income and Southeast Asian ethnicity and Type 2 diabetes. Similarly, two papers investigated how GS could be used to identify populations at risk of smoking and influenza (Amerson, 2014; Kimura et al., 2011).

GS systems can be used for outreach once at-risk populations have been identified. Outreach can lead to interventions that can limit patients' morbidity and mortality as well as reduce their financial burdens while also lowering the cost to public health care systems (Farr & Evans, 2005; Lanza et al., 2007; Sharma et al., 2010). While there is a great opportunity for using GS in health care outreach efforts, the limited number of papers found shows the lack of previous research in this area. Additionally, limited research was found on the use of GS systems for health care and spatial analysis.

The spatial analysis that was reviewed considered GS systems' ability to improve clustering analysis and the ability to better analyze smaller area geographies.

This review demonstrates that previous research found GS systems to be a valuable tool for evidence-based health research. However, the amount of research into the use of these systems is still lacking, particularly in relation to the spatial components of health. Further research needs to be conducted into how GS systems can better identify disease clusters. This research could better answer questions about the correlations between SES, lifestyle, and disease.

Many of the papers are approaching a decade old, and there is a need for understanding how GS systems can be used in conjunction with new technologies such as smartphones, social media, cloud computing, and personal health monitoring devices. There also needs to be more investigation of how GS systems can be used with big data such as health insurance claims, electronic health records, data from social media, and other consumer databases. GS systems could be used to better coordinate outreach with primary care physicians and used with social media to better target market individuals at higher risks of disease. More research needs to be done on how GS systems can serve as a proxy for traditional measures of SES that come from public sources.

In addition to the understating of new technologies, there are new health threats that have evolved since these papers were published. Research needs to take place that investigates the role of GS systems in addressing the opioid epidemic and other more recent health crises. How can these tools be used to address new issues that have developed since previous research was conducted?

Continued investigation into GS systems could improve the ability to address community health by better identifying unknown at-risk populations and improving outreach, intervention, and disease prevention. This research should consider the role of other new spatial technologies. New improvements in public health could be made by considering the spatial relationship between SES and health. GS presents an opportunity to better define and understand these complex relationships.

Chapter 4 Identifying Communities at Risk of Opioid Related Mortalities Utilizing Spatial Rules Based Association Data Mining and Geodemographic Segmentation

Background

The United States is in the midst of an opioid crisis that has evolved over the last 20 years. According to the Centers for Disease Control and Prevention (CDC), the nation is in what the organization considers to be the third wave of the opioid crisis (*Understanding the Epidemic | Drug Overdose | CDC Injury Center*, 2018). The first wave began in the 1990s with the increased prescribing of opioid pain relievers by physicians, which led to increases in opioid related mortalities during the 2000s (Kolodny et al., 2015). The second wave was associated with an increase in the use of the illicit drug heroin in 2010, which was followed in 2013 by a third wave of the epidemic associated with synthetic opioids such as fentanyl (*Understanding the Epidemic | Drug Overdose | CDC Injury Center*, 2018).

In 2017, 67.8 percent of U.S. drug overdoses were related to opioids (47,600 opioid related deaths) (Scholl, 2019). There has been a recent rise in the death rate attributed to synthetic opioids. Between 2016 and 2017, the unintentional overdose mortality rates involving synthetic opioids rose 45.5 percent (5.5 to 8.0 deaths per 100,000) (CDC, 2017). Figure 23 shows the mortality rate by opioid drug classification between 1999–2017 (CDC, 2017).

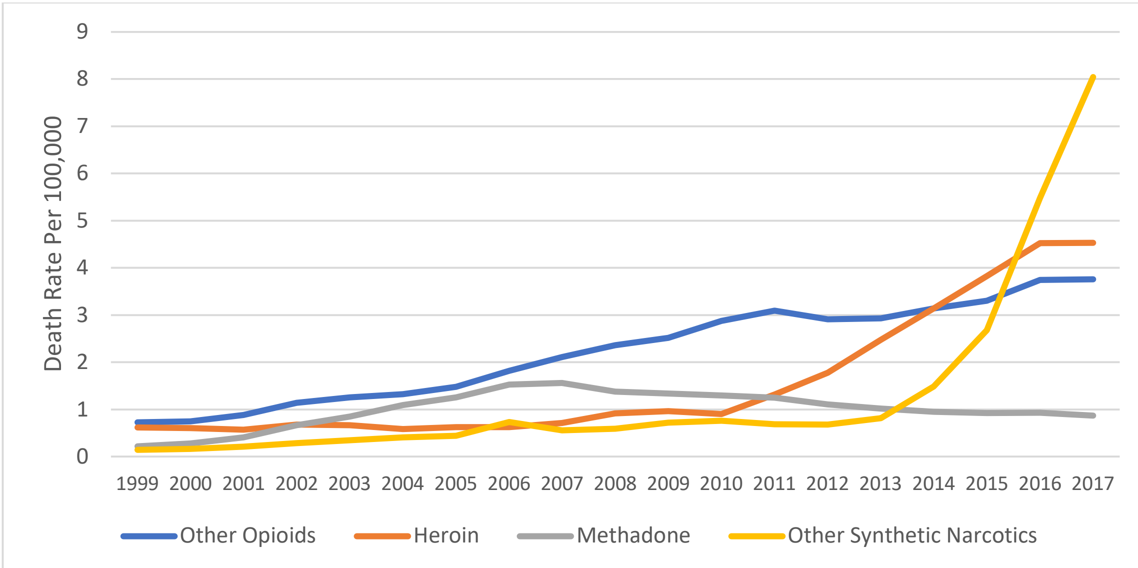

Figure 23. U.S. Annual Rate of Opioid Mortalities by Opioid Type, 1999-2017

Previous geographic research related to opioid misuse investigated the spatial, temporal, and demographic trends of the opioid epidemic (Curtis et al., 2006; Dasgupta et al., 2008; Gladstone et al., 2015; Jalal et al., 2018; McDonald et al., 2012; Sauber-Schatz et al., 2013). Likewise, geographic studies used spatial statistics to investigate the spatial distribution of opioid overdoses, deaths, and prescriptions (Brownstein et al., 2010; Cerdá et al., 2013, 2017; Hester et al., 2012; Kerry et al., 2016; Modarai et al., 2013; Rossen et al., 2014). All these efforts provided insight that could improve prevention and treatment efforts. However, no previous studies of the opioid crisis have used geodemographic segmentation (GS) systems as a variable to represent socioeconomic status (SES) and lifestyle.

Geodemographic segmentation systems are datasets developed by private firms that marketing and other research professionals use to define and distinguish between groups of consumers. The systems leverage multiple data sources such as publicly available, government-collected data such as the American Community Survey, credit reports, population surveys conducted by private research firms, and consumer purchasing data. GS systems suggest that where someone lives says something about who someone is (R. Harris et al., 2005). Some examples of these systems include Experian's Mosaic, ESRI's Tapestry, CACI's Acorn, Nielsen Claritas' PRIZM, and Beacon Dodsworth's P^2 (*Acorn—The smarter consumer classification | CACI*, n.d.; *Claritas MyBestSegments*, 2017; *Esri—Tapestry*, n.d.; *Geodemographic Classification P2 People & Places*, 2017; *Mosaic USA Consumer Lifestyle Segmentation by Experian*, n.d.).

Previous research investigated the application of GS systems in health-related fields. GS systems were evaluated as a method for studying the relationship of socioeconomic deprivation to health outcomes and using GS as an alternative to using publicly available government measures of deprivation (Iyen-Omofoman et al., 2011; Sharma et al., 2010; Douglas & Szatkowski, 2013; Nnoaham et al., 2010; Sheringham et al., 2009; Cheyne et al., 2013; Xin Zhang et al., 2013; Lin et al., 2015; Wiggans et al., 2015; Wright & Polack, 2006). They were studied as a way to identify populations at risk of negative health outcomes (Farr & Evans, 2005; Powell, Tapp, Orme et al., 2007; Amerson, 2014; Kimura et al., 2011; Tomlinson et al., 2011; Petersen et al., 2009). Research was also conducted to show GS's uses for improving spatial analysis of health related issues (Drewnowski et al., 2014; Grubesic et al., 2014; Xingyou Zhang et al., 2013). Finally, an investigation was done in the use of GS systems to improve health care outreach (Jennings et al., 2012; Moss et al., 2009; Powell, Tapp, & Sparks, 2007; Waqar et al., 2012).

The information found in GS systems goes beyond what is found in datasets maintained by public organizations such as the U.S. Census. GS is focused on classifying groups by their lifestyles. This includes information about where they shop and what they buy, how they spend their free time, their preferred media habits, their family and social structures, and financial characteristics. This information is used by firms to identify new customers, potential business locations, and marketing strategies. However, it can also allow for more efficient, more targeted, and cost-effective health care (Lanza et al., 2007).

This research used the CDC's Multiple Causes of Death database, a large national database of mortality data, to demonstrate the use of GS systems for identifying populations at risk of the opioid crisis. This dataset allowed for counts of mortalities to be gathered by different temporal periods, geographic areas, demographics, and by different causes of mortality based on ICD-10 classifications.

This paper presents a methodology for using GS to improve targeted prevention, outreach, and treatment using the CDC's population level data. This is important given the evolution of the crisis, which introduced laws that decreased the availability of prescription opioid drugs. This legislation resulted in a transition of some users from prescription opioids to heroin. To meet the new demand for heroin and counterfeit prescription opioids, illicit opioid drugs began to be adulterated with more powerful synthetic opioids. This resulted in an increase in mortality due to synthetic narcotics.

This methodology is particularly useful when analyzing population level data. It can allow policymakers and public health officials to strategically conduct prevention and treatment strategies based on the association between lifestyle and mortality risk.

Methods

Data

Several sources of data were used in the research. Death rates attributed to opioid drugs were collected from the CDC's National Vital Statistics System mortality (NVSS-M) multiple causes of death dataset via the WONDER online database (CDC, 2017). Data were pulled for the years 2015–2017 and aggregated by county. The data were collected using the underlying cause of death codes X40–X44, which pulls data for deaths with the underlying cause of "drug poisonings (overdose) unintentional." Deaths caused by different opioids were collected using ICD-10 codes; T40.1 (heroin) represented deaths attributed to the illicit drug heroin, T40.2 (other opioids) represented deaths due to prescription semi synthetic opioids such as hydrocodone and oxycodone, and T40.4 (other synthetic narcotics) represented drugs such as fentanyl.

The geodemographic segmentation data used were ESRI's Tapestry for 2016 (*Esri—Tapestry*, n.d.). This system classifies geographic areas by their population's demographics and consumer habits into 67 unique lifestyle segments. Sources for the ESRI Tapestry include: Census 2010; the American Community Survey; ESRI's demographic updates; Experian's ConsumerView database; and consumer surveys, such as the Survey of the American Consumer from GfK MRI.

Data were collected for all three opioid drug classifications and joined to the U.S. Census 2010 TIGER/Line county feature class in ESRI ArcMap 10.6. The death rates for each county were continuous and needed to be converted into a nominal data format to conduct spatial rules based association data mining. This was done in ArcMap by adding a field to represent the counties' death rates as low, low medium, medium, medium high, and high. The fields' nominal value was based on the quantile value of the death rates for each drug class. See Table 5.

Table 5. Quantiles of Opioid Deaths Per 100,00 by Drug Type

					Quantile Value (Deaths Per 100,000)				
	n	**Average**	**Median**	**STD**	**L**	**LM**	**M**	**MH**	**H**
T40.1 (Heroin)	367	7.7	6.5	5.7	0.5-3.2	3.3-5.4	5.5-7.8	7.9-1.2	11.3-43.8
T40.2 (Other Opioids)	413	6.9	5.1	6.4	0.5-3.0	3.1-4.2	4.3-6.1	6.2-9.1	9.2-50.7
T40.4 (Other Synthetic Narcotics)	432	11.1	8.1	9.3	0.4-4.0	4.1-6.8	6.9-10.7	10.8-16.7	16.8-71.6

Additional data relating to county level demographics and opioid prescribing rates were collected from several national government agencies including the CDC, the U.S. Census, and the Bureau of Labor Statistics. Details of the data collected can be found in Table 6. The socioeconomic variables represented gender, education level, age, employment, race, and poverty. These additional variables were converted to nominal values based on their quantile ranking

Table 6. Data Sources Used in Study

Dataset	**Variable**	**Sources**
Opioid Mortality Rates	T40.1 (Heroin) T40.2 (Other Opioids) T40.4 (Other Synthetic Narcotics)	CDC WONDER Database Multiple Causes of Death, 2015-2017
Socioeconomic Characteristics	Tapestry	ESRI, 2018
	Rural-Urban Classification	CDC, 2013
	Percent Minority Percent Disabled	CDC, Social Vulnerability Index, 2016
	Median Age Percent High School Graduate Percent Poverty Percent Male Percent Female	Census, American Community Survey, 2017
	Opioid Prescribing Rate	CDC, 2017
	Medicare Opioid Prescribing Rate	Center for Medicare and Medicaid Statistics, 2016
	Unemployment Rate	Bureau of Labor Statistics, 2017

Analysis

Spatial rules based association data mining is an exploratory form of analysis focused on knowledge discovery with its emphasis being to generate hypotheses as opposed to testing them, which is the goal of common statistical techniques. This type of data mining is sometimes referred to as market basket analysis due to the fact that retailers frequently use this technique to identify like products that are purchased together and offer them grouped as deals, promotions, or at strategic locations within stores.

There are three important parts of a rule: the antecedent (X), the consequent (Y), and the interestingness of the rule comprised of three parts (support%, confidents%, lift). Support measures the frequency of the antecedent in the dataset. The confidence is how often the occurrence of the consequent occurs given the antecedent or frequency of the rule. The lift measures the likelihood of the consequent given the antecedent. A lift of 1 would mean that the variables are not associated. A lift greater than 1 would indicate a positive correlation: less than one would indicate a negative association.

$$X \rightarrow Y \text{ (support\%, confidence\%, lift)}$$

The ESRI Tapestry included a possibility of 67 nominal values. The software used for rules association data mining was SPSS Modeler 18.1. The rules associations were conducted using an Apriori algorithm. The minimum antecedent support was set to one, the minimum confidence was set to 25, and the maximum number of antecedents was set to one.

The criteria for the interestingness of each rule were based on the values of the consequent, confidence, and lift. Consequents were represented by the mortality rate, and antecedents were represented by the GS or demographic variables. The consequents needed to have a nominal quantile value of low or high. The confidence for rules with low consequent values needed to be greater than or equal to 60.0 percent, and the confidence for rules with high consequent values needed to be greater than or equal to 40.0 percent. The lift for all rules needed to be greater than two.

Results

The analysis identified 18 different rules of interest between the GS data and death rate quantile across the three different opioid drug classifications (Table 3). The segmentations associated with high mortality include Salt of the Earth, Modest Income Homes, The Great Outdoors, Diners & Miners, Rooted Rural, and Southern Satellites. The segmentations associated with low mortality include Boomburbs, The Elders, Enterprising Professionals, American Dreamers, Metro Renters, and Up and Coming Families.

The segmentation 6B Salt of the Earth was consistently associated with high mortality for all drugs, and 10B Rooted Rural was consistently associated with other opioids and other synthetic narcotics. Boomburbs was consistently associated with low mortality in all three classes of opioid mortality (Table 3). The results for the Salt of the Earth were: for heroin (7.084, 50.00, 2.514): for other opioids (5.569, 43.478, 2.163): and for other synthetic narcotics (11.111, 43.75, 2.198) The results for the Rooted Rural were: for other opioids (2.179, 88.889, 4.423): and for other synthetic narcotics (1.62, 71.429, 3.588). The measures for all the other associations of interest can be seen in Table 7.

Table 7. Rules of Interest between Mortality Quantile and Tapestry Segmentation

Drug Classification	Consequent	Antecedent	Instances	Support %	Confidence %	Lift
T40.1 (Heroin)	Low	1C Boomburbs	9	2.452	88.889	4.469
T40.1 (Heroin)	Low	9C The Elders	5	1.362	60	3.016
T40.1 (Heroin)	High	6B Salt of the Earth	26	7.084	50	2.514
T40.1 (Heroin)	High	12D Modest Income Homes	4	1.09	50	2.514
T40.1 (Heroin)	High	5E Midlife Constants	7	1.907	42.857	2.155
T40.1 (Heroin)	High	6C The Great Outdoors	7	1.907	42.857	2.155
T40.2 (Other Opioids)	Low	1C Boomburbs	9	2.179	66.667	3.358
T40.2 (Other Opioids)	Low	2D Enterprising Professionals	6	1.453	66.667	3.358
T40.2 (Other Opioids)	Low	7C American Dreamers	5	1.211	60	3.022
T40.2 (Other Opioids)	High	10C Diners & Miners	10	2.421	100	4.976
T40.2 (Other Opioids)	High	10B Rooted Rural	9	2.179	88.889	4.423
T40.2 (Other Opioids)	High	6B Salt of the Earth	23	5.569	43.478	2.163
T40.2 (Other Opioids)	High	10A Southern Satellites	33	7.99	42.424	2.111
T40.4 (Other Synthetic Narcotics)	Low	1C Boomburbs	7	1.62	71.429	3.588
T40.4 (Other Synthetic Narcotics)	Low	3B Metro Renters	8	1.852	62.5	3.14
T40.4 (Other Synthetic Narcotics)	Low	7A Up and Coming Families	18	4.167	72.222	3.628
T40.4 (Other Synthetic Narcotics)	High	10B Rooted Rural	7	1.62	71.429	3.588
T40.4 (Other Synthetic Narcotics)	High	6B Salt of the Earth	48	11.111	43.75	2.198

Identifying segmentations with the spatial rules based association data mining approach was not completely sufficient for identifying at-risk populations due to the location dependency of the mortality data. There were counties that had segmentations that were associated with high mortality, but no actual mortality was recorded in the dataset. So, it would be inappropriate to conclude that a location is susceptible to the epidemic based solely on its GS. Therefore, further analysis of the findings was conducted using additional SES variables to better determine the environment of the locations that have a greater propensity for certain drug classifications with their associated GS segments.

This was done in three levels of analysis. The first level of analysis considered the SES variables of GSs based on their association with high or low mortality with no consideration of mortality. No consideration of drug classification was given in the first level of analysis, unlike the second and third. The second level of analysis considered counties that had GSs associated with high or low mortality and had any quantile level of mortality. The third level of analysis was done on counties that have an associated GS and a mortality quantile of high or low. Table 8 lists the counts of counties at the three levels of analysis.

Table 8. Counts of Counties in the Three Levels of Descriptive Analysis Based Segmentations Associated with High and Low Opioid Mortality

		High	**Low**					
		n	**n**					**Total Counties**
Level 1	All County Level Associated Segmentations in the U.S.	1,187	91					1,278
	Drug Classification	Heroin		Other Synthetic Opioids		Other Synthetic Narcotics		
		High	Low	High	Low	High	Low	
		n	n	n	n	n	n	
Level 2	All County Level Associated Segmentations with Mortality Data in the CDC's Database	44	14	75	20	55	33	241
Level 3	All County Level Associated Segmentations with Mortality Data in the CDC's Database with High or Low Quantiles Levels of Mortality	21	11	42	13	26	23	136

First Level of Analysis

The first level of analysis considered the SES variables of GSs based on their association with high or low mortality at the national level. Not all counties reported levels of mortality in the CDC’s data, but certain counties within these segmentations were found to be associated with high or low mortality. The first level of analysis considered counties with segmentations associated with high or low mortality quantiles regardless of whether the counties were found to have mortality. The segmentations associated with high mortality included Salt of the Earth, Modest Income Homes, The

Great Outdoors, Diners & Miners, Rooted Rural, and Southern Satellites. The segmentations associated with low mortality included Boomburbs, The Elders, Enterprising Professionals, American Dreamers, Metro Renters, and Up and Coming Families.

Table 9 lists the descriptive statistics for the first level of analysis. Based on these results counties with segmentations associated with high mortality had a higher mean percentage of disabled (17.5) and high rates of opioid prescribing (74.5). Counties with segmentations associated with lower mortality had lower mean median age (36.8), percentage of poverty (11.7), urban-rural codes (2.3), and unemployment rates (3.9). They had a higher mean median percentage of minorities. Median age was similar between high segmentations and the country as a whole. Medicare opioid prescribing rates and gender were similar for all three groups.

The 2013 Urban-Rural Classification is a scheme created by the CDC National Center for Health Statistics that categorizes counties on a continuum (1 – Large Central Metro, 2 – Large Fringe Metro, 3 – Medium Metro, 4 – Small Metro, 5 – Micropolitan, and 6 – Non-Core).

Table 9. Descriptive SES Variables of Counties with Geodemographic Segmentation Associated with High and Low Opioid Mortality and All U.S. Counties

	GS Associated with High Mortality		**GS Associated with Low Mortality**		**All Counties**	
	n	**Mean**	**n**	**Mean**	**n**	**Mean**
Percent Male	1187	50.0	91	49.8	3140	50.1
Percent Female	1187	50.0	91	50.2	3140	49.9
Median Age	1187	41.8	91	*36.8	3140	41.2
Percent Poverty	1187	17.4	91	*11.7	3140	16.0
Percent High School Graduate	1187	84.3	91	89.1	3140	86.2
Urban-Rural Code	1187	4.8	91	*2.3	3140	4.6
Percent Disabled	1187	*17.5	91	10.6	3140	15.8
Percent Minority	1187	19.5	91	40.1	3140	22.9
Unemployment Rate	1187	4.9	91	*3.9	3140	4.6
Medicare Opioid Prescribing Rate	1187	5.4	91	5.7	3140	5.3
Opioid Prescribing Rate	1187	*74.5	91	51.1	3140	64.0

*Variables of interest used to describe mortality

Figure 24 shows the spatial distribution of counties with segmentations associated with high and low opioid mortality in the United States. The counties with segmentations associated with high mortality are shaded red, while counties with segmentations associated with low mortality are shaded in blue. The counties with a high association to mortality have a concentration from the South through the Midwest into the northeastern U.S. This provides some clue as to the location of populations that are potentially vulnerable to opioid mortality. However, this analysis only takes into consideration the counties' segmentation. It does not look at mortality in the analysis. This is done in the second and third levels of analysis.

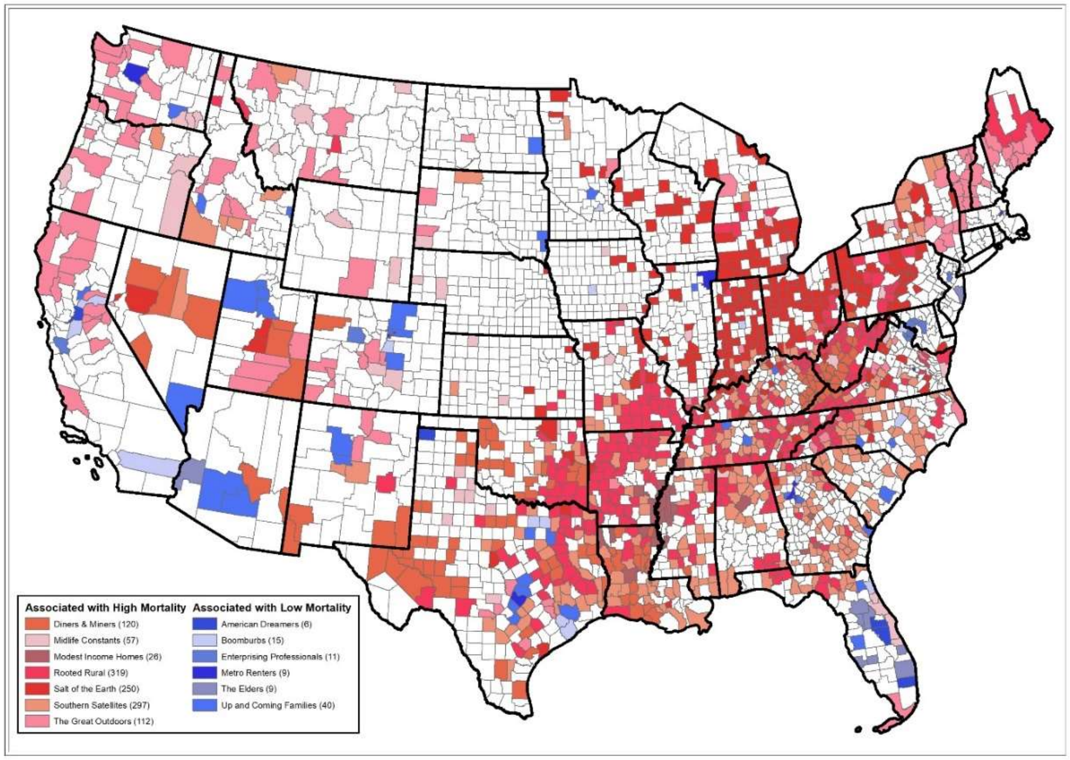

Figure 24. Level 1 Counties with Segmentations Associated with High or Low Mortality

Second Level of Analysis

The second level of analysis considered counties with the above-mentioned lifestyle segmentations but only those counties that had some rate of opioid mortality in the CDC's database. This reduces the number of total counties but gives a comparison between counties associated with segmentation and those having measured mortality in the database. This analysis took into account the location dependency between GS and opioid mortality. Not all counties with a particular segmentation had mortality. Therefore, segmentation alone was not an indication of mortality. Mortality among lifestyle segmentations was thus location dependent.

Tables 10, 20, and 24 present the comparison of the SES variables of counties with segmentations associated with high or low mortality rate quantiles and all the counties with mortality data in the CDC's database for the three opioid classifications. Table 10 shows the SES variable comparisons for heroin. Counties with segmentation associated with high mortality had a higher mean median age (41.7), urban-rural codes (3.4), percentage disabled (15.3), unemployment rates (5.0), and opioid prescribing rates (74.7).

Table 10. Descriptive SES Variables of Counties with Geodemographic Segmentation Associated with Heroin Mortality in CDC Database

	GS Associated with High		**GS Associated with Low**		**All Counties with CDC Data**	
	n	**Mean**	**n**	**Mean**	**n**	**Mean**
Percent Male	44	49.2	14	48.9	367	49.1
Percent Female	44	50.8	14	51.1	367	50.9
Median Age	44	*41.7	14	40.0	367	38.9
Percent Poverty	44	15.3	14	10.5	367	13.5
Percent High School Graduate	44	89.5	14	89.8	367	89.1
Urban-Rural Classification	44	*3.4	14	2.0	367	2.5
Percent Disabled	44	*15.3	14	10.7	367	12.5
Percent Minority	44	19.1	14	37.3	367	31.0
Unemployment Rate	44	*5.0	14	4.2	367	4.4
Medicare Opioid Prescribing Rate	44	5.7	14	5.3	367	5.4
Opioid Prescribing Rate	44	*74.7	14	53.3	367	61.4

*Variables of interest used to describe mortality

Figure 25 shows the concentration of these counties in the eastern U.S. particularly in eastern Ohio and western Pennsylvania. The Tapestry segmentations with a high association to heroin mortality were Midlife Constants, Modest Income Homes, Salt of the Earth, and Great Outdoors.

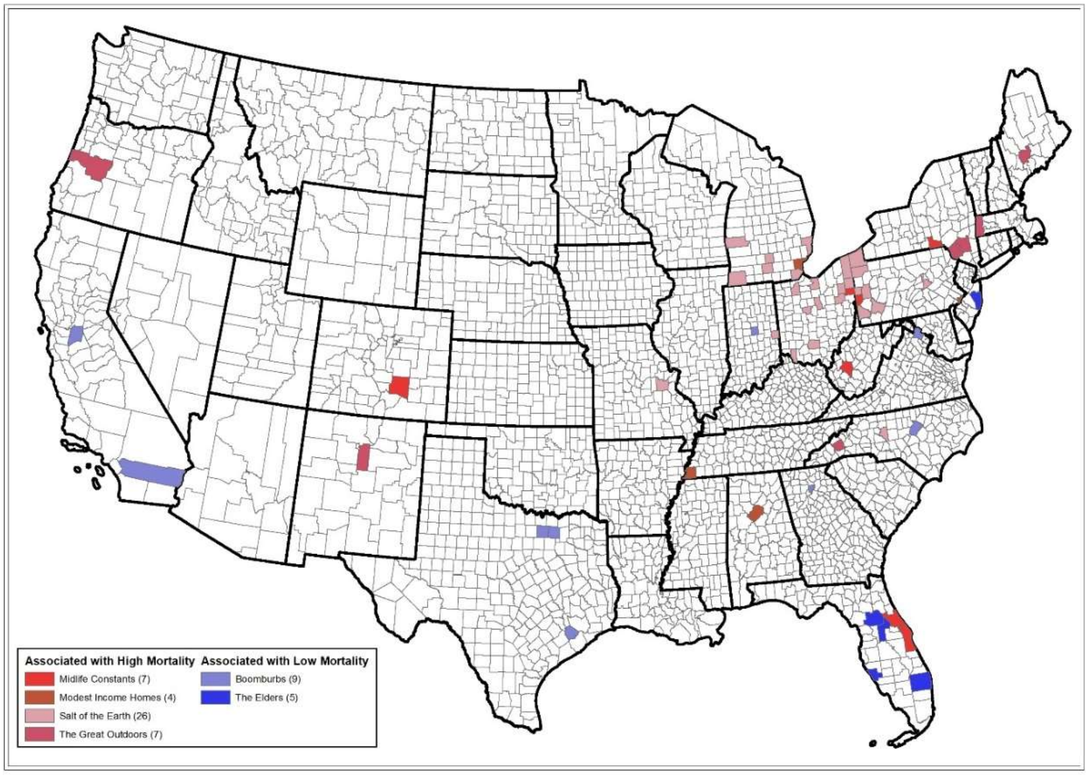

Figure 25. Level 2 Counties with Segmentation Associated with High or Low Heroin Mortality

The spatial distribution of segmentations associated with heroin mortality in the second level analysis provided insight beyond the first level of analysis. One of the primary clusters of segmentations associated with high heroin mortality was located along the Ohio and Pennsylvania border. These states had the largest number of counties found in the second level analysis of heroin mortality. The majority of the counties within the border cluster are of the dominant segmentation Salt of the Earth, but also contain the segmentations Midlife Constants and Modest Income Homes. This was interesting because these segmentations were more rural or suburban according to the Tapestry documentation. The analysis of SES variables indicated that counties with higher Urban-Rural codes, more rural, were more susceptible to heroin mortality. The data in these locations seemed to support this notion. The city of Pittsburgh in Allegheny County was surrounded by this cluster but was not included. Allegheny County had segmentation of Comfortable Empty Nesters and an Urban-Rural Classification of one.

However, this was not the case for all counties. Philadelphia County, PA, located across the state, was an example of an urban county identified as associated with heroin morality in the second level of analysis. The county had a segmentation of Modest Income Homes. It had an Urban-Rural code of one and a high percentage of minorities, 64.7 percent. These findings did not fit with the SES variables identified with high mortality. There were other counties similar to this across the United States. For example, Detroit located in Wayne County, MI, had the segmentation Modest Income Homes, which was associated with high heroin mortality. The county had an Urban-Rural Classification of one and is 50.3 percent minority. Memphis in Shelby County, TN, was another example of this with an Urban-Rural Classification of one and 63.2 percent minority, as was Birmingham in Jefferson County, Alabama. The findings from the analysis of SES variables would not expect these counties to be included due to their urbanicity and a higher percentage of minorities.

Other counties tended to be congruent with the SES variables analysis. Two counties in central Florida, Brevard and Volusia counties, had a segmentation associated with high mortality. These counties were more rural with a low percentage of minorities.

However, both counties had high opioid prescribing rates, 83.7 and 73.3 per 100 persons. This high opioid prescribing rate may have influenced heroin use.

West of the Mississippi River, there were fewer counties represented in the data. Franklin County, MO, is a suburban part of St. Louis. The county was similar in SES characteristics to those expected of counties associated with high heroin mortality and also had a high opioid prescribing rate of 88.1. Pueblo County, Colorado, and Santa Fe County, New Mexico, had Urban-Rural Classifications of four and high prescribing rates of 72.9 and 94.4 per 100 persons, respectively. Both counties had high percentages of minorities at 47.3 and 56.9 percent. Lane County, Oregon was the only West Coast county present in the second level of heroin analysis. The county had an Urban-Rural Classification of three but a low percentage of minorities, 16.9 percent, and a relatively high opioid prescribing rate of 88.1 prescriptions per 100 persons.

Tennessee Department of Health death certificates from the year 2017 were used to further investigate Tapestry segmentation and its relationship to heroin mortality in the state of Tennessee (Tennessee Department of Health, 2017). This was first done for Shelby County, TN, which is an urban county that was identified in the second level analysis as having an association with heroin mortality. The county also had the Tapestry segmentations Modest Income Homes and a heroin mortality quantile value of medium. The findings at the subcounty level using this dataset identified different segmentation than were found with the CDC's county level data than were found at the national level.

Table 11 shows mortality by segmentation and gender. There were 56 total heroin mortalities in the county. The segmentations Emerald City (10) and Family Foundations (8) had the highest levels of mortality. This was interesting because these two segmentations were not identified by the spatial rules based association data mining. Modest Income Homes, the Shelby County's dominant segmentation, had four heroin mortalities, and the other segmentations identified by the rules based association data mining which had a high association with heroin mortality did not appear to be linked to mortality in the county. Males had greater levels of mortality (males 36, females 20).

Table 11. Shelby County Heroin Mortality by Segmentation and Gender

Tapestry	Male	Female	Total
American Dreamers		1	1
Boomburbs	1	1	2
Comfortable Empty Nesters		1	1
Emerald City	6	4	10
Exurbanites	2		2
Family Foundations	6	2	8
In Style	5	1	6
Metro Fusion	2		2
Metro Renters	1		1
Modest Income Homes	2	2	4
Savvy Suburbanites	2	2	4
Soccer Moms	3	1	4
Traditional Living	2	2	4
Up and Coming Families	2	3	5
Young and Restless	2		2
Total	**36**	**20**	**56**

Table 12 shows the average age of decedents of heroin mortality by segmentation. Metro Fusion had the oldest average age (48.0), which was interesting because it is a segmentation associated primarily with younger individuals, but there were low numbers of mortality among this segmentation (2). Comfortable Empty Nesters had an average age of 21.0, which was also interesting because it is a segmentation associated with older individuals, but this may not be significant due to low numbers of mortality (1).

Table 12. Shelby County Heroin Mortality by Segmentation and Average Age

Tapestry	Average Age
American Dreamers	35.0
Boomburbs	24.5
Comfortable Empty Nesters	21.0
Emerald City	45.7
Exurbanites	29.5
Family Foundations	37.3
In Style	34.0
Metro Fusion	48.0
Metro Renters	23.0
Modest Income Homes	36.8
Savvy Suburbanites	44.0
Soccer Moms	38.8
Traditional Living	43.8
Up and Coming Families	32.2
Young and Restless	37.5

Table 13 shows segmentation in relation to the race of the decedents. The majority of the mortality was among whites with the segmentations Emerald City (10) and Family Foundations (8). The highest level of mortality among blacks was in the segmentation Family Foundations (6).

Table 13. Shelby County Heroin Mortality by Segmentation and Race

Tapestry	White	Black	Vietnamese	Total
American Dreamers	1			1
Boomburbs	2			2
Comfortable Empty Nesters	1			1
Emerald City	6	4		10
Exurbanites	2			2
Family Foundations	2	6		8
In Style	6			6
Metro Fusion	1	1		2
Metro Renters	1			1
Modest Income Homes	2	2		4
Savvy Suburbanites	3		1	4
Soccer Moms	4			4
Traditional Living	4			4
Up and Coming Families	4	1		5
Young and Restless	1	1		2
Total	**40**	**15**	**1**	**56**

Shelby County Focused Analysis

Shelby County was further analyzed at the subcounty level. Figure 26 presents the heroin mortality rates by ZIP code in Shelby County symbolized with a red choropleth symbology. In addition to heroin mortality rates, the drug related calls for service rate by ZIP code was mapped using proportionate symbols.

Calls for service are requests that are made through the emergency management system. These can be requests from police in the field or 911 emergency calls made by individuals. Drug related calls consist of two classifications of calls, those related to drug sales and calls related to overdoses. Calls for service are provided by one of the municipalities of Shelby County and do not represent all calls for the whole county.

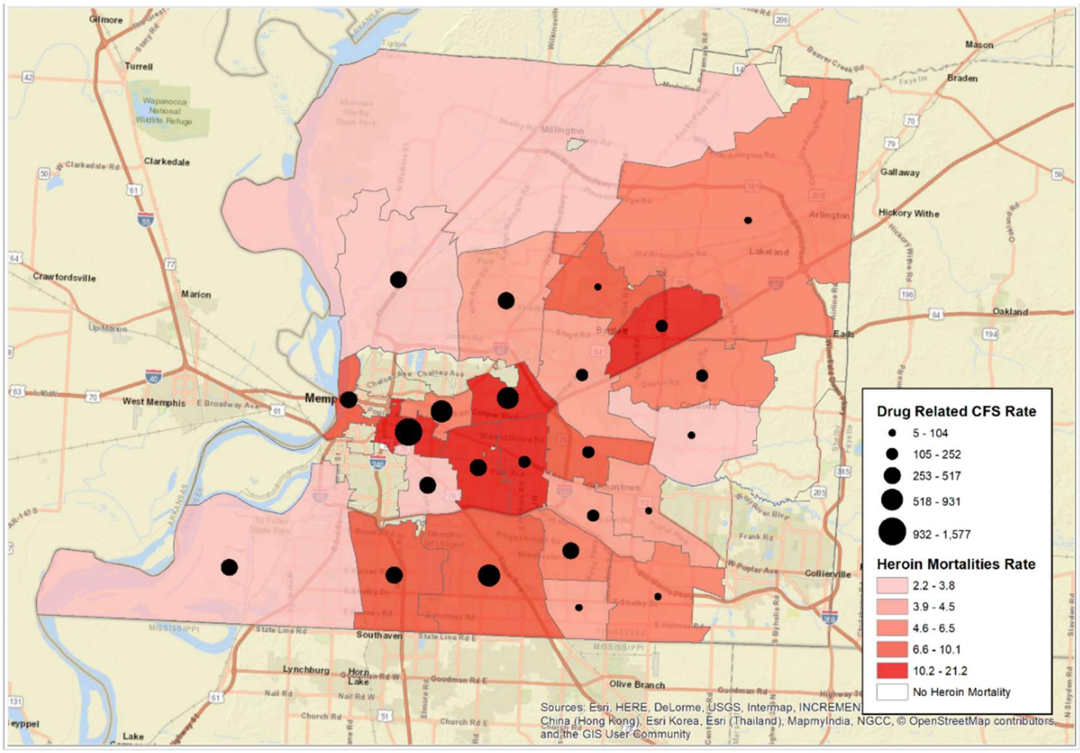

Figure 26. Heroin Mortality Rate by ZIP Code and Drug Related Calls for Services Rate, 2017

Heroin Mortality was concentrated in the population center of the county along the Poplar Corridor in central Shelby County, the southern suburbs such as Whitehaven and Hickory Hill, and in suburbs along the I-40 Corridor. Although calls for service were not representative of the whole county, there appeared to be a concentration of calls along the Poplar Corridor and in the southern suburbs. There seemed to be some spatial relationship between drug related calls for service and heroin mortality in the center of the county.

In addition to exploring Shelby County, the Tapestry segmentation of two other urban counties in Tennessee not identified by the rules based association analysis were analyzed, Davidson and Knox counties. This was done to better understand urban counties in the state that were not found to have an association with heroin mortality. Davidson had the highest number of mortalities in the state for 2017 at 76, and Knox County had the third highest number of mortalities in the state at 43. Davidson County's dominant Tapestry segmentation was Young and the Restless, and it had a heroin mortality quantile of medium high. Knox County had a dominant segmentation Middleburg and a heroin mortality quantile of medium.

Table 14 shows the heroin mortality for Davidson County by gender and segmentation. Most of the mortality occurred among males. Young and the Restless had the largest number of mortalities (29), which is also the county's dominant segmentation. This is interesting in comparison to Shelby County where the largest number of mortalities was found among Emerald City, but the County's dominant segmentation was Modest Income Homes. City Commons had the second largest number of mortalities (13) in Davidson County.

Table 14. Davidson County Heroin Mortality by Segmentation and Gender

Tapestry	**Male**	**Female**	**Total**
Bright Young Professionals	4	1	5
City Commons	9	4	13
Emerald City	4		4
Front Porches	4	5	9
Green Acres	1		1
Metro Renters	2		2
Parks and Rec	1	3	4
Small Town Simplicity	2	3	5
The Great Outdoors	1		1
Top Tier	2		2
Young and Restless	19	10	29
No Address	1		1
Total	**50**	**26**	**76**

Table 15 shows the average age of decedents of heroin mortality by segmentation for Davidson County. Young and the Restless had the highest average age (45.5), which is interesting because this is a segmentation associated with youth. Top Tier had the lowest average age (30.0). This was unexpected since this segmentation is associated with middle age, but there were not many mortalities among this segmentation (2). This may have skewed the results. A similar pattern was seen in Shelby County among average age and segmentation.

Table 15. Davidson County Heroin Mortality by Segmentation and Average Age

Tapestry	**Average Age**
Bright Young Professionals	34.8
City Commons	42.2
Emerald City	44.3
Front Porches	38.3
Green Acres	51.0
Metro Renters	43.0
Parks and Rec	38.0
Small Town Simplicity	37.6
The Great Outdoors	36.0
Top Tier	30.0
Young and Restless	45.5
No Address	32.0

Table 16 shows the heroin mortality in Davidson County by segmentation and race. Young and Restless had the most mortality and was primarily white (white 27, black 2). The second highest mortality was found among City Commons, which was closer to equal between whites and blacks (white 7, black 6). This is to be expected since City Commons is a racially diverse segmentation.

Table 16. Davidson County Heroin Mortality by Segmentation and Race

Tapestry	White	Black	Other	Total
Bright Young Professionals	3	2		5
City Commons	7	6		13
Emerald City	4			4
Front Porches	7	1	1	9
Green Acres	1			1
Metro Renters	2			2
Parks and Rec	3	1		4
Small Town Simplicity	5			5
The Great Outdoors	1			1
Top Tier	2			2
Young and Restless	27	2		29
No Address	1			1
Total	**63**	**12**	**1**	**76**

Table 17 shows the heroin mortality by gender and segmentation for Knox County. The mortality was highest among Middleburg and Rustbelt Traditions (7), which was the County's dominant segmentation. Davidson and Knox had the largest amount of mortality among their dominant segmentations, unlike Shelby County. The majority of mortality was found among males (males 29, females 14).

Table 17. Knox County Heroin Mortality by Segmentation and Gender

Tapestry	**Male**	**Female**	**Total**
Bright Young Professionals	1		1
College Towns	2	2	4
Exurbanites		1	1
Green Acres	1		1
In Style	3	3	6
Middleburg	6	1	7
Modest Income Homes	4	1	5
Old and Newcomers		1	1
Professional Pride	2		2
Rustbelt Traditions	5	2	7
Savvy Suburbanites	2		2
Set to Impress	1		1
Small Town Simplicity	2	2	4
No Address		1	1
Total	**29**	**14**	**43**

Table 18 shows the heroin mortality in Knox County by Tapestry segmentation and average age. Savvy Suburbanites had a high average age (50.5): however, there were only two deaths among the segmentation. Middleburg had the largest amount of mortality (7) and an average age of 41.7. This was similar to the described age of Middleburg in the Tapestry documentation.

Table 18. Knox County Heroin Mortality by Segmentation and Average Age

Tapestry	**Average Age**
Bright Young Professionals	24.0
College Towns	39.3
Exurbanites	31.0
Green Acres	40.0
In Style	26.8
Middleburg	41.7
Modest Income Homes	40.6
Old and Newcomers	56.0
Professional Pride	45.5
Rustbelt Traditions	39.1
Savvy Suburbanites	50.5
Set to Impress	42.0
Small Town Simplicity	40.5
No Address	36.0

Table 19 shows the mortality by segmentation and race for Knox County. The majority of mortality occurred among whites, but this was to be expected since there were low numbers of minorities in East Tennessee. The highest mortality was found among whites in the Middleburg Rustbelt Traditions segmentations (7).

Table 19. Knox County Heroin Mortality by Segmentation and Race

Total	**White**	**Black**	**Total**
Bright Young Professionals		1	1
College Towns	4		4
Exurbanites	1		1
Green Acres	1		1
In Style	6		6
Middleburg	7		7
Modest Income Homes	3	2	5
Old and Newcomers	1		1
Professional Pride	2		2
Rustbelt Traditions	6	1	7
Savvy Suburbanites	1	1	2
Set to Impress	1		1
Small Town Simplicity	4		4
No Address	1		1
Total	**38**	**5**	**43**

Table 20 shows the SES variables comparing the counties with high and low other opioids mortality. Like the SES variables for heroin, counties with segmentations associated with high mortality had higher mean median age (41.1), percentage in poverty (17.0), urban-rural codes (3.7), percentage disabled (18.0), unemployment rates (5.0), and opioid prescribing rates (92.3). These counties also had lower mean percentage of high school graduates (85.2). The counties associated with low mortality had higher mean percentages of minorities (49.2).

Table 20. Descriptive SES Variables of Counties with Geodemographic Segmentation Associated with Other Opioids Mortality in CDC Database

	GS Associated with High		**GS Associated with Low**		**All Counties with CDC Data**	
	n	**Mean**	**n**	**Mean**	**n**	**Mean**
Percent Male	75	49.2	20	49.1	413	49.1
Percent Female	75	50.8	20	50.9	413	50.9
Median Age	75	*41.4	20	36.8	413	38.9
Percent Poverty	75	*17.0	20	10.7	413	14.3
Percent High School Graduate	75	*85.2	20	89.5	413	88.2
Urban-Rural Classification	75	*3.7	20	1.8	413	2.7
Percent Disabled	75	*18.0	20	9.4	413	13.5
Percent Minority	75	15.5	20	*49.2	413	30.9
Unemployment Rate	75	*5.0	20	4.0	413	4.4
Medicare Opioid Prescribing Rate	75	6.1	20	5.2	413	5.8
Opioid Prescribing Rate	75	*92.3	20	42.6	413	68.4

*Variables of interest used to describe mortality

Figure 27 shows the spatial distribution of the counties associated with other opioids mortality in the second level of analysis. Interestingly, these counties differed from the cluster seen for heroin. Counties with segmentations associated with high other opioids mortality were clustered in Appalachia and areas of the South. The Tapestry segmentations with a high association to high other opioids mortality were Diners & Miners, Rooted Rural, Salt of the Earth, and Southern Satellites.

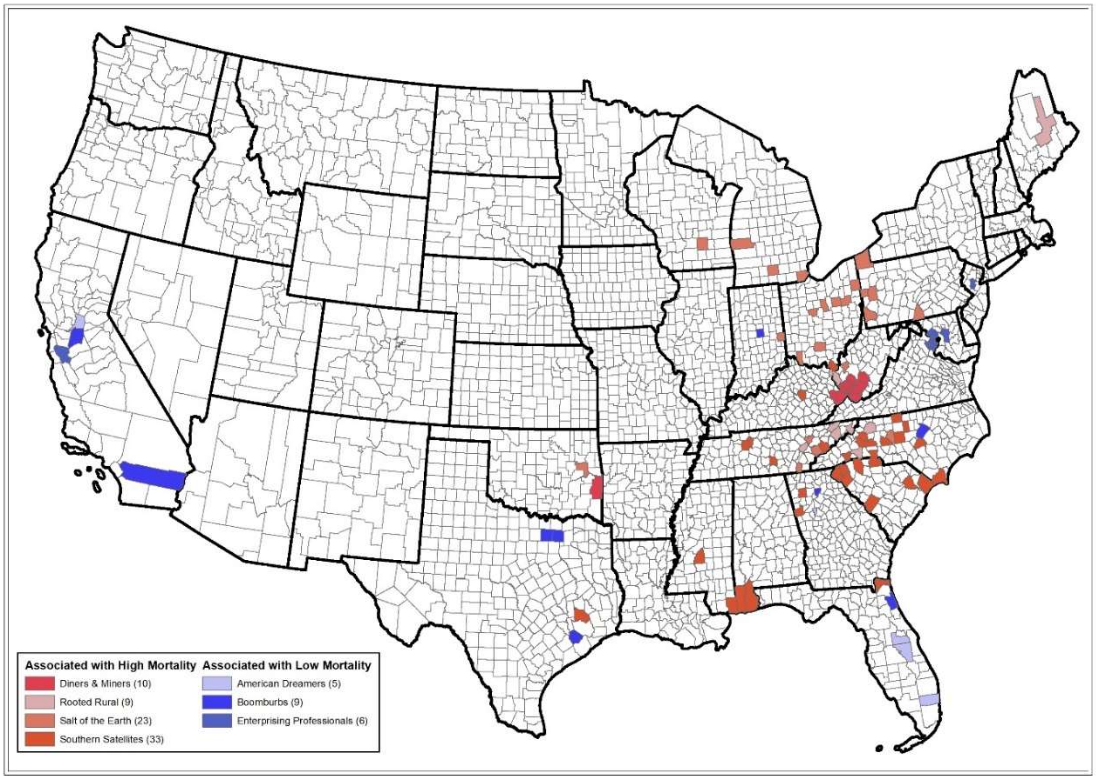

Figure 27. Level 2 Counties with Segmentations Associated with High or Low Other Opioids Mortality

The clustering of segmentations associated with the second level of other opioids mortality had a cluster on the border between Kentucky and West Virginia in the Appalachian Mountain range. The predominant Tapestry segmentation among these counties was Diners and Miners but also consisted of Salt of the Earth and Rooted Rural.

The opioid prescribing rate was extremely high in this area particularly among the Diners and Miners segmentation, ranging from 78.9 to 215.9 prescriptions per 100 persons.

One of the variables which served as an indicator of higher mortality from the SES variables was high unemployment rates. In this cluster unemployment rates ranged from 4.7 to 8.6 percent and were the highest among counties with the Diners and Miners segmentation. As the name of the segmentation implies, the group is heavily employed in natural resource extraction, particularly coal. This industry has seen setbacks in recent years, and decreases in employment among this group may have contributed to growing prescription opioid abuse.

Other areas of Appalachia had segmentations of high mortality. These counties were along the border of Tennessee and North Carolina. These counties predominately had the dominant segmentations Salt of the Earth and Southern Satellites. Unemployment was lower in this cluster compared to the one further north in Appalachia, 3.0 to 6.2 percent. However, opioid prescribing rates were still high with a range between 62.5 and 156.7 prescriptions per 100 persons. The percentage of minorities in these counties was generally low at 4.5 to 34.5 percent.

Mortality data from the Tennessee Department of Health were also used to further explore other opioids mortality. Eleven counties in the state had dominant segmentations associated with high quantile values of other opioids mortality. These included Anderson, Blount, Bradley, Carter, Cheatham, Coffee, Dickson, Greene, Hawkins, Roane, and Sevier counties. The dominant Tapestry segmentations for these counties consisted of Rooted Rural, Salt of the Earth, and Southern Satellites. The state's mortality data for these counties were analyzed by demographic and segmentation to identify differences between the county and subcounty levels.

Table 21 shows the other opioids mortality in the counties identified in the second level analysis by segmentation and gender. The four segmentations with the highest level of mortality were Southern Satellites (29), Salt of the Earth (18), Rooted Rural (14), and Midlife Constants (14). These mortality levels by Tapestry segmentation were similar to those identified by the spatial rules association data mining. This was probably because these counties were more rural and county level dominant segmentations more closely reflect subcounty segmentation due to less diversity of segmentations within counties. Mortality was higher for males than for females (males 61, females 53), but the disparity between male and female mortality was not as great as was seen for heroin using the Tennessee mortality data.

Table 21. Tennessee Counties Identified in Second Level Analysis of Other Opioids Mortality by Segmentation and Gender

Tapestry	**Male**	**Female**	**Total**
Bright Young Professionals	1		1
Comfortable Empty Nesters	2		2
Exurbanites	5	3	8
Green Acres	2	4	6
Hardscrabble Road		4	4
Middleburg		1	1
Midlife Constants	6	8	14
Old and Newcomers	1	2	3
Rooted Rural	10	4	14
Rural Bypasses	4	1	5
Rustbelt Traditions		1	1
Salt of the Earth	8	10	18
Silver & Gold	1		1
Small Town Simplicity	2	2	4
Soccer Moms		1	1
Southern Satellites	17	12	29
The Great Outdoors	2		2
Total	**61**	**53**	**114**

Table 22 shows the average age of other opioids mortality found in the second level of analysis by segmentation. The oldest average age was found for the segmentation Silver and Gold (64.0). This was a segmentation associated with older individuals, but there was only one recorded other opioids mortality. Middleburg had the youngest average age (24.0), but it also had only one mortality. The segmentations with the highest levels of mortality had average ages that were middle-aged and were similar to what was found in the Tapestry documentation (Salt of the Earth 44.0, Southern Satieties 44.1, Rooted Rural 50.0, Midlife Constants 45.3). This was another example of how the rules association data mining identified associations at the county level better in rural counties than in urban due to less diversity at the subcounty level, similar to what was seen with total counts of mortality.

Table 22. Tennessee Counties Identified in Second Level Analysis of Other Opioids Mortality by Segmentation and Average Age

Tapestry	Average Age
Bright Young Professionals	37.0
Comfortable Empty Nesters	39.5
Exurbanites	47.8
Green Acres	51.3
Hardscrabble Road	33.8
Middleburg	24.0
Midlife Constants	45.3
Old and Newcomers	38.7
Rooted Rural	50.0
Rural Bypasses	43.8
Rustbelt Traditions	32.0
Salt of the Earth	44.0
Silver & Gold	64.0
Small Town Simplicity	47.3
Soccer Moms	46.0
Southern Satellites	44.1
The Great Outdoors	47.5

Table 23 shows other opioids mortality in relation to segmentation and race. The majority of the mortality occurred among whites (107), but this was to be expected since East Tennessee had a low number of minorities. This was seen above in the table showing Knox County heroin mortality, but Shelby County still had high heroin mortality among whites even though the county has high levels of minorities.

Table 23. Tennessee Counties Identified in Second Level Analysis of Other Opioids Mortality by Segmentation and Race

Tapestry	White	Black	Unknown	Total
Bright Young Professionals		1		1
Comfortable Empty Nesters	2			2
Exurbanites	7	1		8
Green Acres	6			6
Hardscrabble Road	3	1		4
Middleburg	1			1
Midlife Constants	14			14
Old and Newcomers	3			3
Rooted Rural	14			14
Rural Bypasses	5			5
Rustbelt Traditions		1		1
Salt of the Earth	18			18
Silver & Gold	1			1
Small Town Simplicity	2	1	1	4
Soccer Moms	1			1
Southern Satellites	28	1		29
The Great Outdoors	2			2
Total	**107**	**6**	**1**	**114**

Table 24 shows the comparison of the SES variables for high and low other synthetic narcotics mortality. Counties with segmentations associated with high mortality had a higher mean median age (41.8), urban-rural code (4.0), percentage disabled (15.6), unemployment rate (5.0), and prescribing rate (71.4). Counties with segmentations associated with low mortality had a higher mean percentage of minorities (41.0).

Table 24. Descriptive SES Variables of Counties with Geodemographic Segmentation Associated with Other Synthetic Narcotics Mortality in CDC Database

	GS Associated with High		**GS Associated with Low**		**All Counties with CDC Data**	
	n	**Mean**	**n**	**Mean**	**n**	**Mean**
Percent Male	55	49.5	33	49.3	432	49.1
Percent Female	55	50.5	33	50.7	432	50.9
Median Age	55	*41.8	33	35.1	432	39.5
Percent Poverty	55	14.4	33	12.8	432	13.4
Percent High School Graduate	55	88.8	33	89.4	432	89.2
Urban-Rural Classification	55	*4.0	33	1.7	432	2.7
Percent Disabled	55	*15.6	33	10.2	432	13.1
Percent Minority	55	9.0	33	*41.0	432	27.1
Unemployment Rate	55	*5.0	33	3.8	432	4.4
Medicare Opioid Prescribing Rate	55	5.2	33	5.9	432	5.4
Opioid Prescribing Rate	55	*71.4	33	51.8	432	64.0

*Variables of interest used to describe mortality

Figure 28 shows the spatial distribution of these counties. The counties demonstrated a clustering pattern with a concentration in eastern Ohio and western Pennsylvania. The segmentations associated with high other synthetic narcotics mortality were Rooted Rural and Salt of the Earth. The segmentations associated with low other synthetics narcotics mortality were Boomburbs, Metro Renters, and Up and Coming Families.

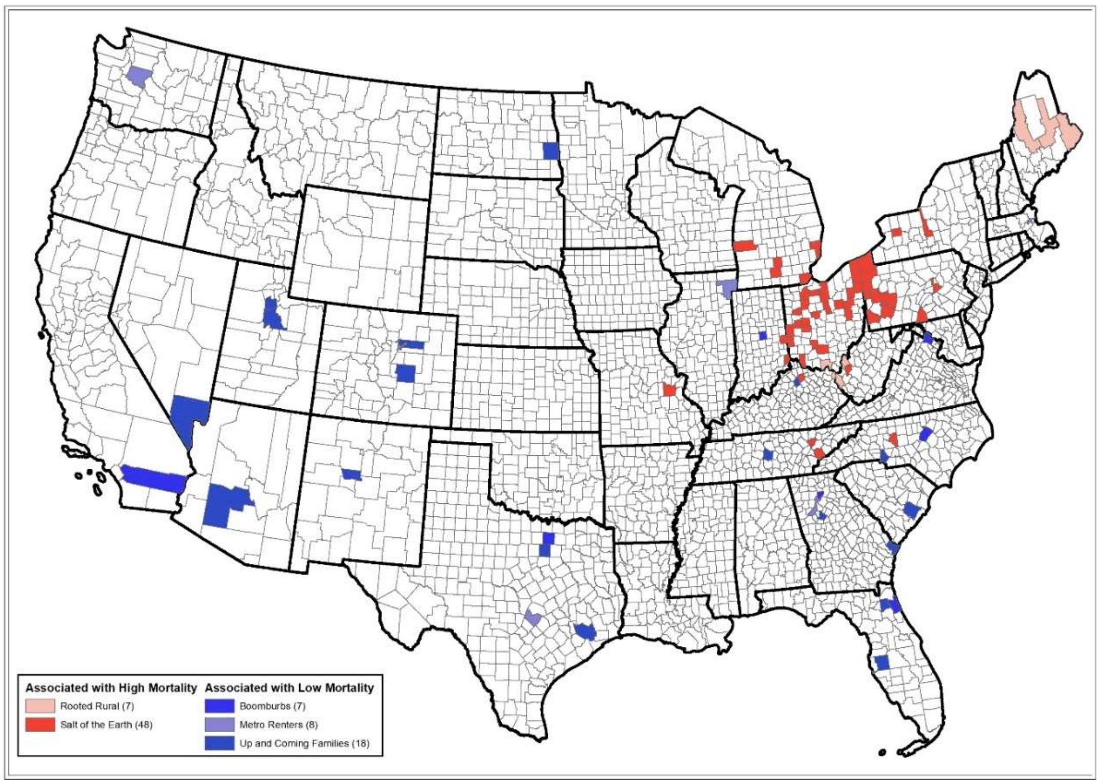

Figure 28. Level 2 Counties with Segmentations Associated with High or Low Other Synthetic Narcotics Mortality

A similar pattern was seen in terms of clustering of the counties with segmentations associated with other synthetic narcotics mortality and those observed for heroin. This was most likely due to fentanyl's use as an adulterant of illicit heroin. However, other synthetic narcotics had a stronger demonstration of clustering than did heroin. The cluster was centered around Ohio and included counties in western

Pennsylvania and parts of Michigan. Most of these counties had a dominant segmentation of Salt of the Earth or Rooted Rural. The counties in this cluster had low percentages of minorities, 2.7 to 23.3 percent. The Urban-Rural Classifications ranged from two to six. There was a wide range of opioid prescribing rates between 43.2 to 111.4 prescriptions per 100 persons. The variation of opioid prescribing rates seems to be independent of Tapestry segmentation.

An additional cluster of three large counties of Rooted Rural in the second level of analysis was found in Maine. These counties were rural and had similar SES characteristics to the cluster found in the Midwest with low minorities and moderate prescribing rates.

The Tennessee mortality data were also used to investigate associations found in the rules based association data mining and other synthetic narcotics mortality. Two counties (Anderson and Blount) were found to have an association with the drug classification in the second level of analysis. Anderson County had the other synthetic narcotics mortality quantile of medium high, and Blount County's mortality quantile for the drug classification was low medium. Both counties had the dominant Tapestry segmentation Salt of the Earth.

Table 25 shows the mortality due to other synthetic narcotics by Tapestry segmentation and gender for both counties. Mortalities were highest among males (18). The segmentation with the highest level of mortality is Salt of the Earth (11). Salt of the Earth is the dominant segmentation for both Anderson and Blount counties. This further supports the notion that the Tapestry segmentation was better at predicting at the county level in rural counties with more homogeneity of their populations.

Table 25. Tennessee Counties Identified in Second Level Analysis of Other Synthetic Narcotics Mortality by Segmentation and Gender

Tapestry	**Male**	**Female**	**Total**
Comfortable Empty Nesters	2	1	3
Exurbanites	4	1	5
Midlife Constants	2	1	3
Rooted Rural	1	1	2
Rural Bypasses	1	1	2
Rustbelt Traditions		1	1
Salt of the Earth	7	4	11
Southern Satellites	1		1
Total	**18**	**10**	**28**

Table 26 shows the mortality rates for both counties by average age and segmentation. All of the segmentations had average ages around middle-aged except Comfortable Empty Nesters (34.7) and Midlife Constants (32.0), which were slightly lower than expected. However, these segmentations only had three deaths each.

Table 26. Tennessee Counties Identified in Second Level Analysis of Other Synthetic Narcotics Mortality by Segmentation and Average Age

Tapestry	**Average Age**
Comfortable Empty Nesters	34.7
Exurbanites	46.0
Midlife Constants	32.0
Rooted Rural	40.5
Rural Bypasses	47.0
Rustbelt Traditions	43.0
Salt of the Earth	39.9
Southern Satellites	53.0

Table 27 shows the mortality for both counties by segmentation and race. Whites had the highest levels of mortality (26). However, this was not unexpected since the two counties are located in East Tennessee, which as stated above, is an area with low minority populations.

Table 27. Tennessee Counties Identified in Second Level Analysis of Other Synthetic Narcotics Mortality by Segmentation and Race

Tapestry	**White**	**Black**	**Total**
Comfortable Empty Nesters	3		3
Exurbanites	4	1	5
Midlife Constants	3		3
Rooted Rural	2		2
Rural Bypasses	2		2
Rustbelt Traditions	1		1
Salt of the Earth	10	1	11
Southern Satellites	1		1
Total	**26**	**2**	**28**

Third Level of Analysis

The third level of analysis takes into consideration the mortality quantile as being high or low and the segmentation. Therefore, the number of counties was further reduced, but this allowed for more focused analysis. Table 4 above list the counts of counties at the third level of analysis. Tables 28, 29, and 33 present the SES variables in the third level of analysis.

Table 28 shows SES variables of counties having a GS associated with high or low mortality and high and low quantiles of the heroin mortality. The mean percentage of disabled (15.3) and prescribing rate (75.6) were higher for the counties with a GS associated with high mortality and a quantile of high mortality compared to all counties with a GS associated with high or low heroin mortality. The counties with a GS associated with lower mortality and having a low quantile of heroin mortality had a higher mean percentage of minorities (40.0).

Table 28. Descriptive SES Variables of Counties with Geodemographic Segmentation Associated with Heroin Mortality and High or Low Mortality Quantiles

	GS Associated with High Mortality and High Quantile		**GS Associated with Low Mortality and Low Quantile**		**All Counties with GS Associated with High or Low**	
	n	**Mean**	**n**	**Mean**	**n**	**Mean**
Percent Male	21	49.3	11	48.9	58	49.1
Percent Female	21	50.7	11	51.1	58	50.9
Median Age	21	42.1	11	39.5	58	41.3
Percent Poverty	21	15.1	11	10.5	58	14.1
Percent High School Graduate	21	89.0	11	89.5	58	89.6
Urban-Rural Classification	21	3.4	11	2.0	58	3.1
Percent Disabled	21	*15.3	11	10.6	58	14.2
Percent Minority	21	17.7	11	*40.0	58	23.5
Unemployment Rate	21	5.1	11	4.2	58	4.8
Medicare Opioid Prescribing Rate	21	5.7	11	5.4	58	5.6
Opioid Prescribing Rate	21	*75.6	11	53.7	58	69.6

*Variables of interest used to describe mortality

Figure 29 shows the spatial distribution of these counties. There was a cluster of counties with GS associated with high heroin mortality and high quantiles of mortality in southern Michigan, Ohio, and eastern Pennsylvania. These counties were present in the second level of analysis but are significant due to their high quantile of heroin mortality in addition to having segmentations associated with high mortality.

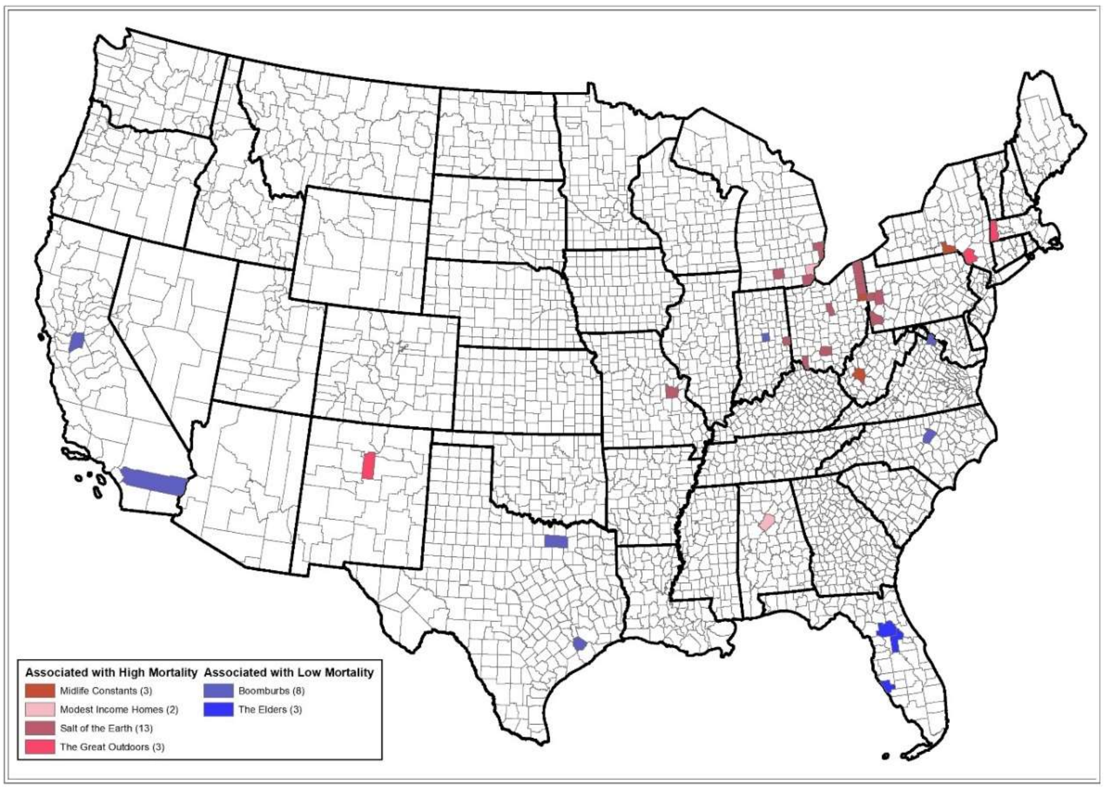

Figure 29. Level 3 Counties with Segmentations Associated with High or Low Heroin Mortality

The counties of the cluster on the Ohio and Pennsylvania border were predominately the Salt of the Earth. They had low minorities and were mostly rural with moderately high prescribing rates. The counties in Michigan were also Salt of the Earth and were similar in terms of SES variables except for Wayne County, which is urban and has a high percentage of minority. Another exception was Calhoun County, MI, which had a high prescribing rate compared to other counties in the clusters, 101.4 prescriptions per 100 persons.

Kanawha County, West Virginia, location of the state's capital, Charleston, was also identified in the third level of heroin mortality analysis. Although a state capital, the area was still considered rural with an Urban-Rural Classification of four. The county had a low percentage of minorities, 12.1 percent, and a high opioid prescribing rate of 94.9 prescriptions per 100 persons. The counties from all the mentioned clusters had moderately high levels of percentage disabled.

Table 29 shows the counties with GS associated high and low other opioids mortality and having quantiles of high or low mortality. The counties having GS associated with high other opioids mortality and a high quantile of mortality had higher mean Urban-Rural Classifications (4.0), percentage disabled (20.6), and prescribing rates (100.8). The counties also had a lower mean percentage of high school graduates (83.6). The counties with GS associated with low other opioids mortality and low quantiles of mortality had a higher mean percentage of minorities (51.8) and lower poverty (10.2).

Table 29. Descriptive SES Variables of Counties with Geodemographic Segmentation Associated with Other Opioids Mortality and High or Low Mortality Quantiles.

	GS Associated with High Mortality and High Quantile		**GS Associated with Low Mortality and Low Quantile**		**All Counties with GS Associated with High or Low**	
	n	**Mean**	**n**	**Mean**	**n**	**Mean**
Percent Male	42	49.3	13	49.0	95	49.2
Percent Female	42	50.7	13	51.0	95	50.8
Median Age	42	42.0	13	36.8	95	40.5
Percent Poverty	42	18.9	13	*10.2	95	15.7
Percent High School Graduate	42	*83.6	13	90.0	95	86.1
Urban-Rural Classification	42	*4.0	13	1.6	95	3.3
Percent Disabled	42	*20.6	13	8.8	95	16.2
Percent Minority	42	11.4	13	*51.8	95	22.6
Unemployment Rate	42	5.2	13	3.9	95	4.7
Medicare Opioid Prescribing Rate	42	6.0	13	5.0	95	5.9
Opioid Prescribing Rate	42	*100.8	13	39.6	95	81.9

*Variables of interest used to describe mortality

Figure 30 shows counties with GS associated with high mortality and high quantiles of mortality located in Appalachia along the Kentucky and West Virginia border and the Tennessee and North Carolina line. There was a cluster of counties in

West Virginia that has the dominant segmentation Diners and Miners. This group had high opioid prescribing rates, 60.9 to 215.9 per 100 persons. This was interesting because other counties identified nearby had much lower prescribing rates, 61.6 to 78.9, but different segmentations, Salt of the Earth, Southern Satellites, and Rooted Rural. These counties were located in West Virginia, eastern Kentucky, and southern Ohio. However, there was a cluster in the southern part of Appalachia between Tennessee and North Carolina with the same segmentations but higher prescribing rates, 73.7 to 125.3. All the counties in these clusters had low percentages of minorities and were rural. The percentage of disabled was also high for both of these clusters, 13.0 to 33.3 percent.

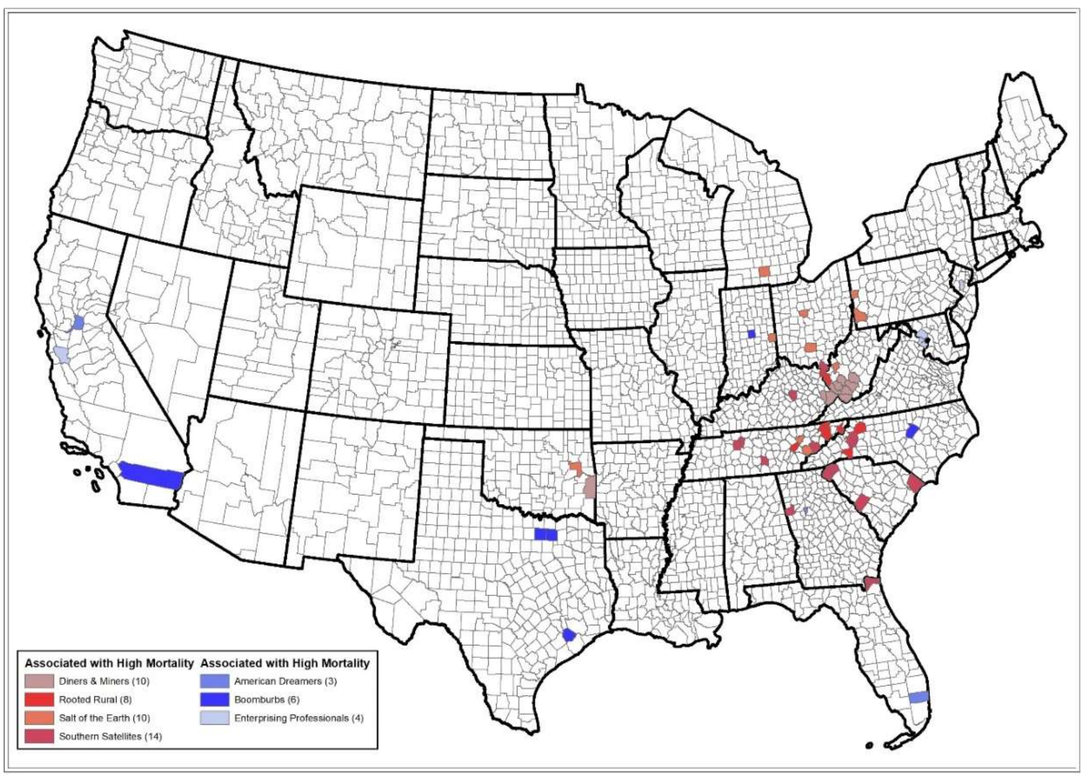

Figure 30. Level 3 Counties with Segmentations Associated with High or Low Other Opioids Mortality

The results of the third level analysis of the other opioids mortalities were further explored with the mortality data from the Tennessee Department of Health. Ten counties were identified in the third level of analysis in the state: Anderson, Blount, Carter, Cheatham, Coffee, Dickson, Greene, Hawkins, Roane, and Sevier counties. These counties all had high other opioids mortality quantiles, and their Tapestry segmentations included Rooted Rural, Salt of the Earth, and Southern Satellites. The counties in the third level of analysis of Tennessee were the same that were in the second level except for Bradley County in southern East Tennessee, which had a mortality quantile of medium high.

Table 30 shows the mortality counts by segmentation and gender for the counties identified in Tennessee in the third level of analysis. These results were similar to what was seen in the second level of analysis since there was only one county difference. The majority of the mortality was among males (60). Southern Satellites had the largest number of mortalities (27), followed by Salt of the Earth (17), Rooted Rural (14), and Midlife Constants (14).

Table 30. Tennessee Counties Identified in Third Level Analysis of Other Opioids Mortality by Segmentation and Gender

Tapestry	**Male**	**Female**	**Total**
Bright Young Professionals	1		1
Comfortable Empty Nesters	2		2
Exurbanites	5	3	8
Green Acres	2	4	6
Middleburg		1	1
Midlife Constants	6	8	14
Old and Newcomers	1	2	3
Rooted Rural	10	4	14
Rural Bypasses	4	1	5
Rustbelt Traditions		1	1
Salt of the Earth	7	10	17
Silver & Gold	1		1
Small Town Simplicity	2	2	4
Soccer Moms		1	1
Southern Satellites	17	10	27
The Great Outdoors	2		2
Total	**60**	**47**	**107**

Table 31 shows the average age of the other opioids mortalities by segmentation in the counties of Tennessee identified by the third level of analysis. Middleburg had the youngest average age (24.0), and Green Acres had the highest (51.3). The ages seemed to reflect what would be expected from the Tapestry documentation except for Middleburg, which seemed to be lower. However, there was only one death in this segmentation.

Table 31. Tennessee Counties Identified in Third Level Analysis of Other Opioids Mortality by Segmentation and Gender

Tapestry	**Average Age**
Bright Young Professionals	37.0
Comfortable Empty Nesters	39.5
Exurbanites	47.8
Green Acres	51.3
Middleburg	24.0
Midlife Constants	45.3
Old and Newcomers	38.7
Rooted Rural	50.0
Rural Bypasses	43.8
Rustbelt Traditions	32.0
Salt of the Earth	44.3
Silver & Gold	64.0
Small Town Simplicity	47.3
Soccer Moms	46.0
Southern Satellites	43.6
The Great Outdoors	47.5

Table 32 shows the mortalities by segmentation and race for the counties identified in the third level of analysis. The majority of the mortalities were among whites (101), which should be expected due to the demographics of East Tennessee.

Table 32. Tennessee Counties Identified in Third Level Analysis of Other Opioids Mortality by Segmentation and Race

Tapestry	White	Black	Unknown	Total
Bright Young Professionals		1		1
Comfortable Empty Nesters	2			2
Exurbanites	7	1		8
Green Acres	6			6
Middleburg	1			1
Midlife Constants	14			14
Old and Newcomers	3			3
Rooted Rural	14			14
Rural Bypasses	5			5
Rustbelt Traditions		1		1
Salt of the Earth	17			17
Silver & Gold	1			1
Small Town Simplicity	2	1	1	4
Soccer Moms	1			1
Southern Satellites	26	1		27
The Great Outdoors	2			2
Total	**101**	**5**	**1**	**107**

Table 33 shows the SES variables of counties with GS associated with high or low other synthetic narcotics mortality and quantiles of high or low mortality. Counties with GS associated with high mortality for this drug classification and high quantiles of mortality had high mean Urban-Rural Classification (4.4), percentage disabled (16.4), and opioid prescribing rates (70.7). Counties with GS associated with low mortality and having low quantiles of mortality had high mean percentages of minority (42.4).

Table 33. Descriptive SES Variables of Counties with Geodemographic Segmentation Associated with Other Synthetic Narcotics Mortality and High or Low Mortality Quantiles

	GS Associated with High Mortality and High Quantile		GS Associated with Low Mortality and Low Quantile		All Counties with GS Associated with High or Low	
	n	**Mean**	**n**	**Mean**	**n**	**Mean**
Percent Male	26	49.6	23	49.6	88	49.4
Percent Female	26	50.4	23	50.4	88	50.6
Median Age	26	41.9	23	34.7	88	39.3
Percent Poverty	26	14.8	23	12.3	88	13.8
Percent High School Graduate	26	88.4	23	89.5	88	89.1
Urban-Rural Classification	26	*4.4	23	1.7	88	3.2
Percent Disabled	26	*16.4	23	9.7	88	13.6
Percent Minority	26	8.1	23	*42.4	88	21.0
Unemployment Rate	26	5.2	23	3.7	88	4.5
Medicare Opioid Prescribing Rate	26	4.7	23	6.2	88	5.4
Opioid Prescribing Rate	26	*70.7	23	50.4	88	64.1

*Variables of interest used to describe mortality

Figure 31, like Figure 28, shows a cluster of counties around Ohio with GS associated with Other Synthetic Narcotics and high quantiles of mortality. The segmentations with an association with high mortality were limited to Rooted Rural and Salt of the Earth. The counties in the cluster were predominately rural or suburban. There was a wide variation in opioid prescribing rates, 43.8 to 92.0 prescriptions per 100 persons. This cluster was most likely associated with heroin use in the area.

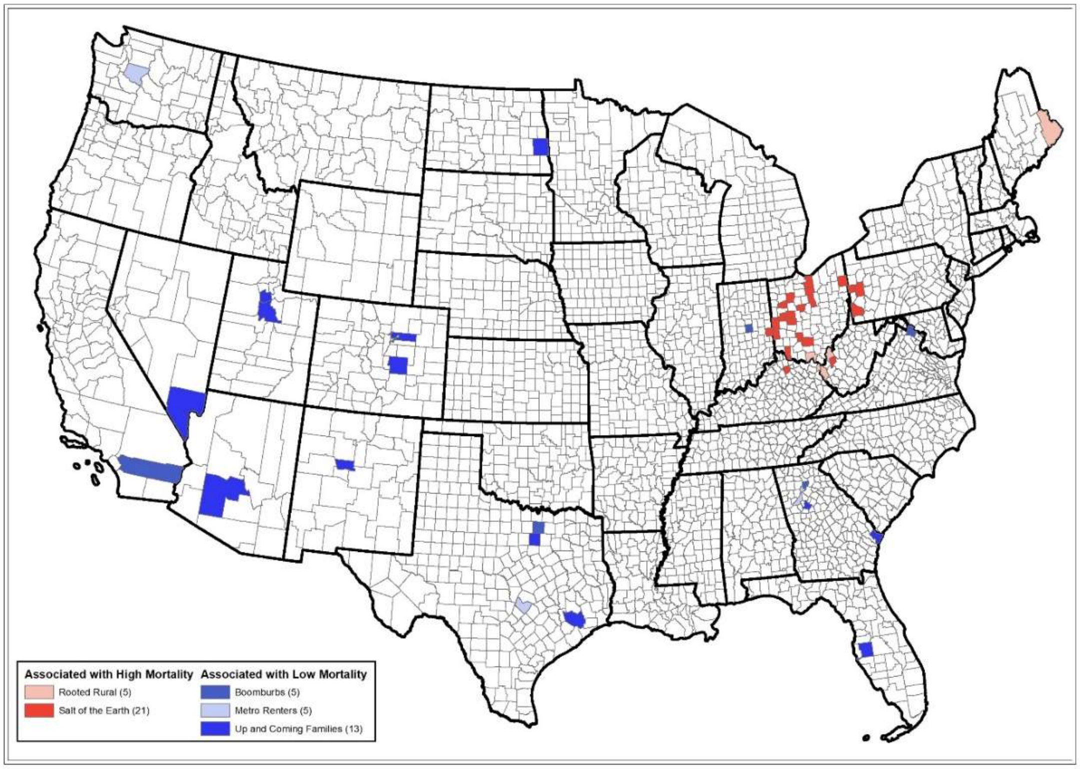

Figure 31. Level 3 Counties with Segmentations Associated with High or Low Other Synthetic Narcotics Mortality

Summarization of Results

The analyses at the national and Tennessee state levels found slightly different results in terms of Tapestry segmentation for each of the classes of opioid drugs. The state level analysis of mortality counts helped bring to light some of the limitations of conducting spatial rules association data mining of county data at the national level. Namely, it was more difficult to use dominant Tapestry segmentation to describe urban counties with more diverse populations. This had different impacts on the results of the analysis among different drug classes and locations.

This was the case for heroin for which different Tapestry segmentations were identified using the national and state level analysis. Salt of the Earth, Modest Income

Homes, Midlife Constants, and the Great Outdoors were identified as being associated with heroin at the national level. Further investigation of the state level data found some different Tapestry segmentations. Davidson, Shelby, and Knox counties had the three highest levels of mortality for the study period, respectively. Shelby County had the second highest number of heroin mortalities, but it was the only county identified in the national level analysis. This was due to how rules association data mining identified associations between mortality quantile and Tapestry segmentations.

Shelby County's dominant segmentation was Modest Income Homes and it had a high mortality quantile. This segmentation and quantile combination along with other counties across the country resulted in Shelby County being associated with high heroin mortality. Davidson and Knox counties had medium high and medium heroin mortality quantiles. Davidson having a lower quantile may have been a result of the time periods investigated, 2015-2017 at the national level and 2017 for the state level. It may also have been due to the difference between looking at rates at the national level versus absolute counts at the state level. Davidson and Knox also had different Tapestry segmentations, Young and the Restless and Middleburg. These county level variables resulted in the counties not being identified in the analysis.

Shelby County's dominant segmentation, Modest Income Homes, was not reflected in the mortality counts which were highest for Emerald City. Modest Income Homes was a segmentation associated with urban African American communities, whereas Emerald City was associated with whites. The second highest mortality count in Shelby was among Family Foundations which was associated with higher levels of African Americans. Davidson's dominant Tapestry segmentation was the same as the highest count of mortality, Young and the Restless. This was probably due to the large influx of young workers into the area over the past few years. Knox County's dominant Tapestry and the highest level of mortality were also the same.

Analysis of the state mortality's demographic data showed that heroin was more common among younger, white, males. The national level demographics showed that heroin was more common among slightly older individuals: however, this was population level data. The state level data indicated that heroin was more urban, while the national level data indicated it was slightly less urban. Unemployment rates were higher in the national level data as were opioid prescribing rates.

The analysis of other opioids demonstrated a different pattern than was seen for heroin. The state level data showed that the other opioids mortality was most common among the Tapestry segmentations Southern Satellites (29), Salt of the Earth (18), Rooted Rural (14), and Midlife Constants (14). This was more like the national level findings, with the exception of Midlife Constants and Diners and Miners. Middle Life Constants was not identified by the national level analysis, and there were no large populations of Diners and Miners in Tennessee.

Other opioids analysis between the national and state levels of investigation may have been the same since other opioids was more of a rural drug than was heroin. The mean Urban-Rural Classification from the SES analysis was 3.7 for other opioids and 3.4 for heroin. Heroin and fentanyl are both drugs more associated with urban environments (Rhodes et al., 2019). This allowed the analysis at the national level to better perform and be validated by the state data. Heroin was more associated with males, but the state data showed that while males were impacted greater, females were also a component of the mortality. The state data also showed that whites comprised the majority of other opioids mortality. The SES variables also showed a relationship between other opioids mortality and high percentages of poverty, percentage disabled, and unemployment rates, as well as high opioid prescribing rates. Low other opioids mortality was also seen to be associated with high percentages of minority populations, similar to heroin.

Other Synthetic narcotics mortality was associated with Salt of the Earth in both the national and state level analysis. Rooted Rural was also identified in the national level analysis but had less of a presence in the state level. Males made up the majority of the mortality, but females were also present similar to in other opioids. This could be the result of synthetic opioids being used as an adulterant in counterfeit prescription drugs. Whites also comprised the majority of the deaths, similar to those for the other three classes of opioids. Also similar to the other opioids was the link in the SES variables between high mortality and high prescribing rates, higher percentage disabled, and higher mean median age that were seen for other synthetic narcotics. Other synthetic narcotics also had the hieghest mean rural score of the three drug classifications at 4.0. This was unexpected due to the connection between other synthetic narcotics and heroin, which is considered an urban drug.

In terms of age, the SES variables found all three drug classifications were associated with higher mean median age. These ages were all middle-aged (41.4-41.8). The state level data varied, but certain segmentations such as Young and the Restless had high mortality counts in Davidson County.

Using Geodemographic Segmentation for Health Intervention, Prevention, and Treatment

The spatial rules based association data mining found two segmentations with an association with high mortality in multiple drug classifications, Salt of the Earth and Rooted Rural. Salt of the Earth was associated with high mortality rates in all three drug classes. Rooted Rural was associated with high mortality rates in the other opioids and other synthetic narcotics classifications. Figure 32 shows the distribution of the segmentations at the county level in the United States. These counties are geographically distributed from Maine to eastern Texas, with large concentrations in the Midwest in rural counties.

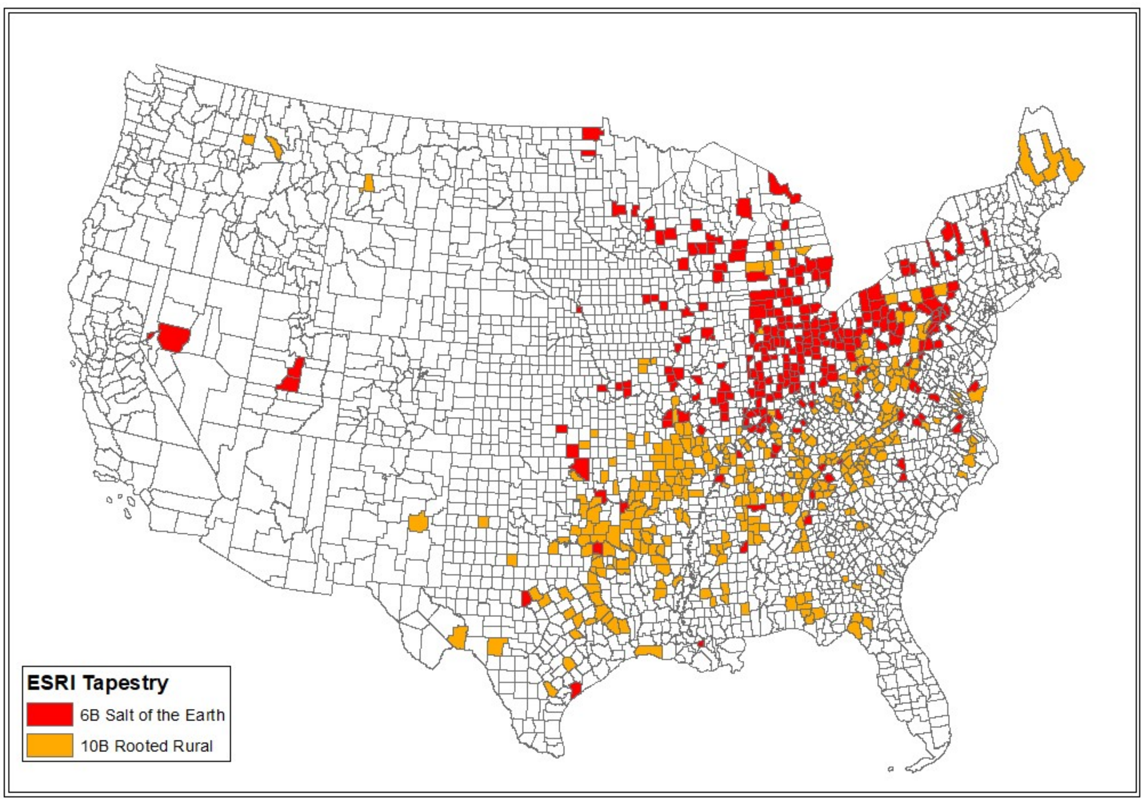

Figure 32. Spatial Distribution of Salt of the Earth and Rooted Rural by County. This map does not consider mortality.

The ESRI Tapestry documentation provides information on how to market to these two segmentations. This same information can be used to conduct more efficient health intervention, prevention, and treatment. For example, the Tapestry documentation describes Salt of the Earth as rural residents who tend to be older and have household incomes slightly above the national average. They have high rates of homeownership which are priced 25.0 percent below the national average. Forty percent have only a high school education, and their employment is associated with construction, manufacturing, and related service industries.

In terms of marketing preferences, Salt of the Earth is cost conscious, brand loyal, health conscious, and focused on buying American. They are late adopters of new products. They like outdoor activities and own recreational vehicles. They tend to own satellite dishes and receive the internet through DSL due to their rural locations. They are do-it-yourselfers and prefer to do business in person. They enjoy the outdoors and are averse to new technology.

According to the documentation, the Rooted Rural segmentation is employed heavily in the forestry industry. Nine in ten are non-Hispanic whites. They enjoy outdoor activities similar to Salt of the Earth. When not outdoors, they watch TV and spend time with pets. Their communities are influenced by faith, traditional gender roles, and family history.

Rooted Rural has a do-it-yourself mentality and repair their own vehicles and ATVs. They are right leaning in their political values. They are thrifty and use coupons and buy generic. They are not fashion conscious of the latest clothing styles. They pay bills in person and are not comfortable with computers and smartphones. However, still half have high-speed internet.

In terms of media preferences, they own satellite dishes and watch Country Music Television, the History Channel, and the Game Show Network. They listen to faith-based radio, country, and gospel music. There are a high number of Medicare recipients in the segmentation, and they frequent Walgreens pharmacies.

This type of information provides insight into how best to conduct health outreach to these two segmentations. This can be of value when trying to inform individuals about opioid drug treatment and abuse prevention. The ESRI Tapestry documentation indicates that both groups are not users of the latest technology. This suggests that it would be less effective to reach these groups through social media or other mobile technologies. However, both groups are outdoors enthusiasts. This might suggest that it would be best to distribute literature at outdoors related events and retail establishments.

Both segmentations rely on satellite television for entertainment. This might be the best advertising medium to reach these groups with public service announcements as opposed to print media such as newspapers or magazines. The ESRI documentation indicates that Rooted Rural is focused on faith and family. This may indicate that an intervention that relies on social cognitive theory is appropriate. For example, individuals from the Rooted Rural segmentation may be more heavily influenced by their friends and environment, and it may be best to include these elements in an intervention strategy.

The documentation also mentioned that the Rooted Rural segmentation contains a high number of Medicare recipients and frequently use Walgreens pharmacies. The Medicare program could provide an avenue to provide information about prescription opioid abuse and treatment options. Likewise, since the segmentation frequents Walgreens pharmacies, these locations may be good places to conduct a health intervention to prevent prescription opioid abuse.

Both segmentations are fans of country music and auto racing. A strategy for reaching these groups could be to hire a famous country music singer or racecar driver to perform in public service announcements about the dangers of prescription and illicit opioid abuse and provide information about treatment options. Both segmentations live in remote rural areas. This type of information could be used for improved treatment strategies such as rural emergency care or mobile overdose prevention.

Salt of the Earth and Rooted Rural are both Tapestry segmentations associated with middle-aged, rural, white populations. The state level data brought to light the impact of opioids on younger and African American populations. Shelby County had a large number of mortalities with the segmentation Family Foundation, and Davidson County had a large number of Young and the Restless.

Family Foundations shop at warehouse clubs and low-cost retailers. They listen to R&B radio and gospel and prefer to watch BET. Their preferred recreational activity is basketball. An intervention to this group may be focused on illicit opioids such as heroin. It may warn of the dangers of fentanyl contamination. Public service announcements may come through BET or preferred radio stations in urban areas. A basketball star could be used to deliver messages. The segmentation is also family-oriented, living in multi-generational households. It may be best to include family members when disseminating information about the dangers of illicit drugs.

There was a large amount of heroin mortality among Young and the Restless in Davidson County. This is a young population. They are heavy smartphone users, and few have landlines. They use their cellphones for almost all daily activities such as paying bills, shopping, social media, and listening to music. They are fans of contemporary music. They purchase natural/organic foods but still frequent fast food restaurants. They watch VH1 and Comedy Central. An intervention to this group should focus on heroin and fentanyl contamination as well. Social media and other mobile technologies should be leveraged to warn about the dangers of opioid drugs. Public service announcements could feature comedians on Comedy Central or contemporary musicians on VH1.

Conclusions

This study analyzed population mortality data from the CDC using spatial rules based association data mining. Using this analysis, mortality was found to be associated with several ESRI Tapestry segmentations at the county level. This analysis provided clues as to how opioid related mortality by opioid type was associated with Tapestry lifestyle segmentations.

The associations were further explored using Tennessee Department of Health mortality records. This was individual level data that were aggregated to Tapestry segmentations. This technique helped to expose some of the weaknesses of using the CDC's data with Tapestry segmentation. The most significant finding was that county level analysis was more efficient when analyzing rural counties. This was due to the homogeneity of the population in rural counties. Urban counties had more population diversity, which as a result meant the dominant ESRI Tapestry segmentation at the county level did not adequately represent the entire population at the subcounty level.

Several drug classes of opioid drugs were investigated. It was less effective to analyze heroin mortality with the rules association data mining. This is because this drug tends to be more urban, and the population is not adequately represented at the county level with dominant Tapestry segmentations. As a result, the drug appeared to be more suburban in nature in the county level analysis. Subcounty analysis using the Tennessee Department of Health data showed that in the case of Shelby County the dominant segmentation did not represent the majority of heroin mortality but did in Davidson and Knox counties.

Other opioids mortality, which was found to be more rural, was more easily analyzed with the county level analysis and the association data mining. The Tennessee Department of Health data supported the findings of the county level analysis. This is most likely due to the homogeneity of populations in rural counties.

Some similarities were found between segmentation associations at the county and subcounty levels for other synthetic narcotics. In particular, was the presence of Salt of the Earth in both analyses. However, the subcounty analysis found more variation than was seen analyzing the county level Tapestry segmentations.

The county level analysis also showed differences in the regions of the nation most impacted by the epidemic. Areas hit particularly hard by the epidemic were Ohio, southern Wisconsin, and western Pennsylvania. This region was greatly impacted by both heroin and other synthetic narcotics. This is most likely due to the fact of the interrelatedness of these two drugs. Heroin is adulterated with synthetic opioids. Other opioids mortality was more spread out through the country but had a high concentration in rural Appalachian areas of the country, the South, and the Midwest.

Heroin mortality was found to be more urban among younger populations. Other Opioids mortality was associated with more rural and suburban users and was prevalent among older populations. Other synthetic narcotics mortality was also more rural, which was unexpected. This is probably due to the drug's use as an adulterant in counterfeit prescription drugs as well as illicit heroin. All mortality was most prevalent among whites. However, the state data identified some segmentations of African Americans that were at-risk, namely Family Foundations.

Application of Findings

The methodology presented in this paper could be bolstered with the use of new technology such as data mining of electronic health records. Investigating individual level data will more accurately identify lifestyle segmentations associated with disease and contribute to a better understanding of their location dependencies.

Great value can be created by linking health data to marketing data. It can create more efficient diagnosis, treatment, and prevention. Lifestyle segmentation can provide clues for physicians on how to more properly diagnose patients in much the same way these data allow more efficient marketing to consumers. It can also be used in treatment such as rural emergency care and mobile overdose prevention. For example, certain lifestyle segmentations may have higher levels of efficacy to different treatments according to how they live such as those living in remote areas. Approaching a health problem with this type of method would be more cost effective. This could allow policymakers to see better returns on investment in regard to funds put toward public health.

However, before any of this potential can be realized, segmentation data must become a standard component of health data analysis. It should be mined along with electronic health records, hospital discharge data, and mortality records. This paper demonstrates just the tip of the iceberg in terms of what can be done with contemporary analytic software. Additionally, the analysis should be expanded to include data from other fields such as crime, health insurance, and other variables of the built environment. This could provide further information about the nature of diseases and how to best respond.

Another important concept toward the continuation of this research is placing this information in its temporal place. As was noted, the opioid crisis evolved from prescription opioids to heroin and most recently has seen an increase in synthetic opioid mortality. It should be asked which segmentations were the most vulnerable to the progression of the crisis. How did laws and policies affect segmentations differently, and what was the location dependency of this vulnerability? Lifestyle segmentation holds the potential to identify these individuals and intervene to halt the progression of this and future drug crises.

This study was done at the population level. Population studies can be complementary to clinical studies, which have more detailed information on individuals' race, gender, age, and other personal characteristics. Investigation of segmentation data can provide clues and guide further research on individuals. However, population studies using GS can still be helpful in guiding intervention efforts by identifying at-risk populations to target.

This paper explored county level mortality data and found value in using GS systems to identify segmentations at risk of opioid mortality. Future research should include household and patient level GS analysis. ESRI Tapestry is limited to population studies since the smallest geography available is Census block group. Experian Mosaic is a segmentation system that can identify household level lifestyle segmentations. This could be used with patient data, insurance claims, and mortality records to better identify segmentation for intervention.

Electronic health records and patient discharge records could be used to track patients in relation to their lifestyle segmentation. There should also be program evaluation to determine the return on investment of this type of data mining pre and post implementation. More informed policy decisions may lead to reductions in the economic cost of the epidemic. Geodemographic segmentation systems hold great promise for improving the health care system in the future and therefore should be considered a critical component of health care data analysis moving forward.

Chapter 5 Exploratory Analysis of Opioid Related Hospital Discharge and Mortality Records Using Geodemographic Segmentation

Background

Over the past several decades, the United States has been battling an evolving opioid epidemic (CDC, 2018a). In 2017, 68.0 percent of overdoses in the country involved an opioid drug (CDC, 2017). The development of this epidemic came in three waves associated with prescription opioids, heroin, and most recently synthetic opioids such as fentanyl (CDC, 2018a).

This paper examines the impact these drugs had in the state of Tennessee using hospital discharge and mortality records. These results are compared to mortality at the national level using mortality data from the Centers for Disease Control (CDC). ESRI Tapestry LifeMode groups are used as a socioeconomic variable to better understand the opioid related rates and their locations.

Methods

The opioid incidents data used in this study came from three sources. Tennessee Department of Health hospital discharge records and death certificates were used to analyze the rate of opioid related mortality and hospital discharges at the state ZIP code level (Tennessee Department of Health, 2017). These data were queried by ICD-10 and ICD-10-CM codes. These codes were those which related to heroin, other opioids, or other synthetic narcotics. The codes were part of the diagnosis in hospital discharge records or a cause of fatality on death certificates. Data for mortalities caused by the same opioid classifications were obtained at the county level for the United States from the CDC (CDC, 2017).

All data were collected for the year 2017. Data from the CDC were calculated as rates per 100,000. From that data, rates indicated to be “Unreliable” due to low numbers of deaths or population were removed from the database. Opioid related hospital discharge and mortality rates for Tennessee were calculated per 100,000 using the population numbers from the American Community Survey for 2017 (U.S. Census Bureau, 2019). All county and ZIP code geographic boundaries were based on the 2010 TIGER/Line shapefile boundaries (*TIGER/Line Shapefiles*, 2019).

The geodemographic segmentation data used in this research were ESRI’s Tapestry (*Esri—Tapestry*, n.d.). Geodemographic segmentation data are typically collected for the intent of marketing. However, it has been suggested that these types of data can be used for conducting more efficient health care interventions (Farr & Evans, 2005; Lanza et al., 2007). Tapestry data consist of 67 distinct segmentations that represent a population’s lifestyle, demographic traits, and preferences. These segmentations are grouped into 14 LifeMode groups.

This research was conducted using several different methods at two geographic scales, the Tennessee ZIP code and the United States county level. First, rate maps of opioid related hospital discharges and mortality at the Tennessee ZIP code level were utilized. This was intended to gain an understanding of the basic spatial components of opioid use within the state and identify any visible spatial patterns such as clustering around urban or rural areas of the state.

Analysis of variance was conducted on the mean rates of hospital discharge and mortality data of ZIP codes and counties based on Tapestry LifeMode groupings. The 14 Tapestry LifeModes were used as opposed to using the 67 individual segmentations for both ZIP code and county level analysis. This was due to a lack of statistical significance among the mean rates of segmentations. This is most likely due to similarities between segmentations.

This was followed by a descriptive analysis of the mean rates of opioid related hospital discharges and mortality based on LifeMode. The focus of this analysis was to identify LifeModes and locations with the highest rates of discharge and mortality. This was only done for rates shown to have a statistically significant difference among mean rates between LifeModes in the analysis of variance.

Finally, spatial rules based association data mining was conducted. The goal of this analysis was to identify the differences in the results of the comparison of means and the rules association data mining to further verify LifeModes associated with opioid activity based on drug classification. Association data mining was done using the Apriori algorithm in SPSS Modeler. The models' parameters were set up to have a minimum antecedent support of one and minimum confidence of 40 for each rule. Rules of interest were required to have had a consequent value of high or low and a lift of greater than one.

Results

Analysis of Tennessee Hospital Discharges and Mortality

Rate maps were created for all the Tennessee hospital discharge data. The discharge rate maps demonstrated clustering around urban and rural areas but for different opioid drug classifications. For example, the heroin discharge rates showed clustering around urban centers in the state such as Memphis, Nashville, Knoxville, Chattanooga, and Jackson. See Figure 33. The rate mapping seemed to suggest that heroin related hospital discharges were associated with more urban environments. This could have been the result of more access to illicit heroin in urban areas or greater access to emergency care to treat and thus report heroin related hospitalization.

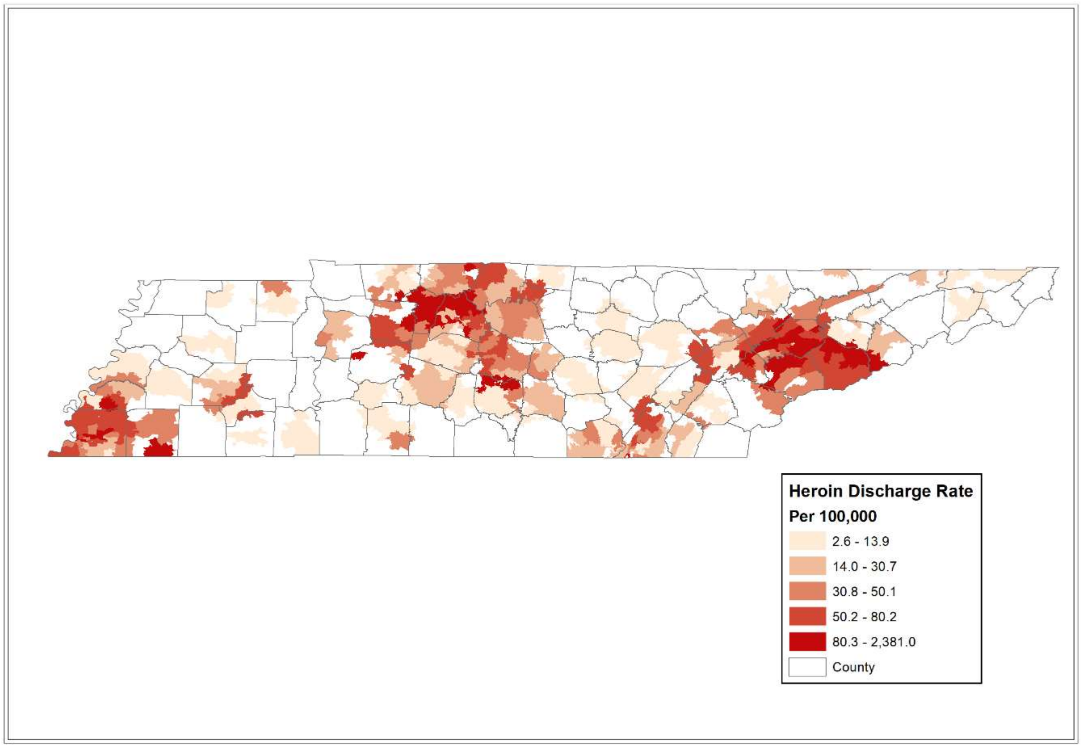

Figure 33. Tennessee Hospital Discharge with Heroin Related Diagnosis Rate Per 100,000

Other opioids discharge rates clustered in an opposite pattern. See Figure 34. Although other opioids discharge rates were present in both urban and rural areas, rural areas of the state had higher other opioids hospital discharge rates. It appeared that these drugs were being abused at higher rates in rural areas as opposed to urban but were still abused in both types of areas.

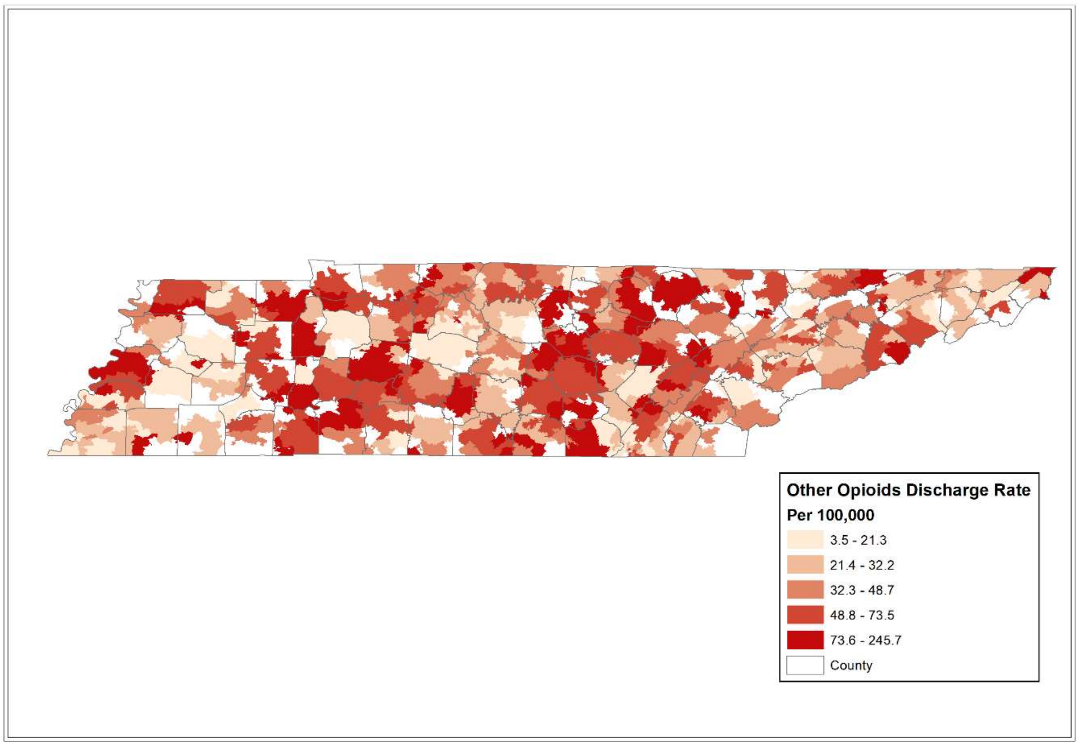

Figure 34. Tennessee Hospital Discharge with Other Opioids Related Diagnosis Rate Per 100,000 by ZIP Code, 2017

The clustering pattern for other synthetic narcotics discharge rates seemed to be more random. See Figure 35. The highest rates for these discharges were in rural areas, but many rural areas had low rates or no discharge rate. Synthetic drugs however still seemed to demonstrate geographic clustering. This could have been an indication of areas where the drugs entered the illicit drug supply as an adulterant.

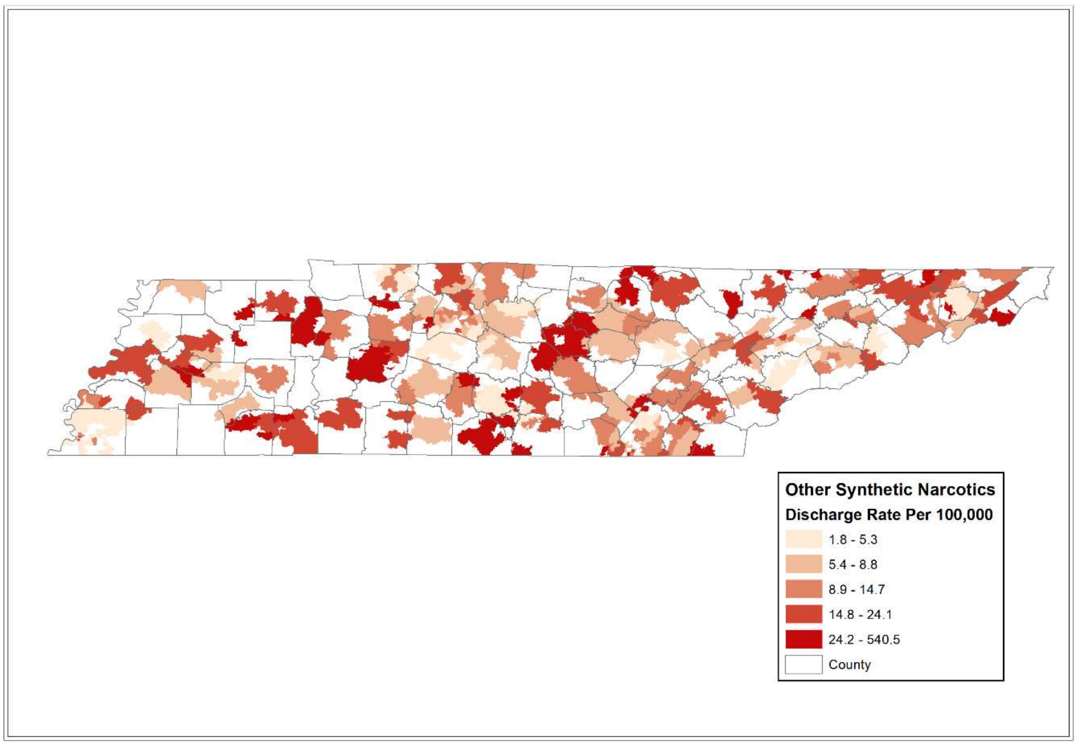

Figure 35. Tennessee Hospital Discharge with Other Synthetic Narcotics Related Diagnosis Rate Per 100,000 by ZIP Code, 2017

Rate maps were also created for Tennessee opioid mortality. The clustering of heroin mortality rates was somewhat similar to those seen for heroin discharge rates. See Figure 36. The clustering tended to be in or near urban centers. However, mortality didn't seem to be as widespread as the discharge rates. There were areas with high rates on urban peripheries. This may have indicated areas where illicit heroin was available, but accessibility to emergency medical treatment was not in the event of an overdose.

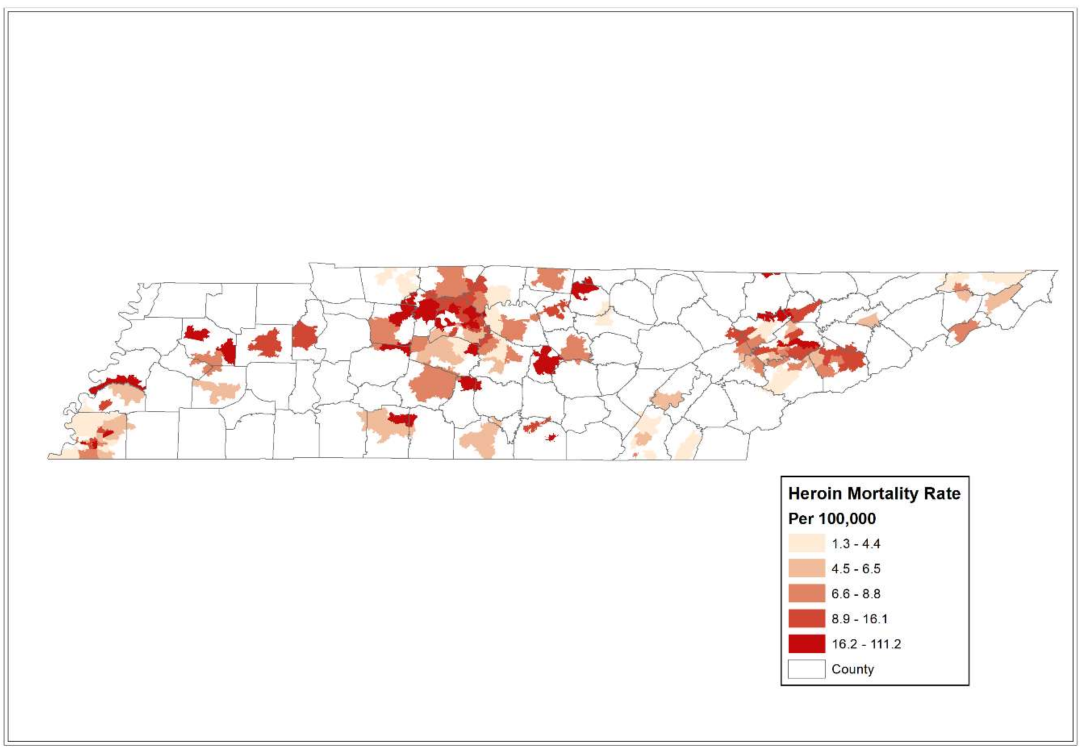

Figure 36. Tennessee Mortality with Heroin Related Cause of Death Rate Per 100,000 by ZIP Code, 2017

Other opioids mortality seemed to be rural, urban, and suburban but in different areas of the state. See Figure 37. In Shelby County, the largest population center of West Tennessee, there appeared to be low rates of other opioids related mortality. This was also true of rural areas in northwestern Tennessee. Some rural areas of southern West Tennessee did have high rates of other opioids mortality. Middle and East Tennessee had areas with high rates found in urban, suburban, and rural areas. There could have been several explanations for the differences between Middle and East Tennessee compared to the western portion of the state. The first possible explanation was demographic. West Tennessee was predominately African American. This may have demonstrated a difference between African Americans' and whites' abuse of prescription opioids. A second related explanation may have been that there were differences in access to medical care. There may have been lower access to medical care and thus prescription opioids in West Tennessee.

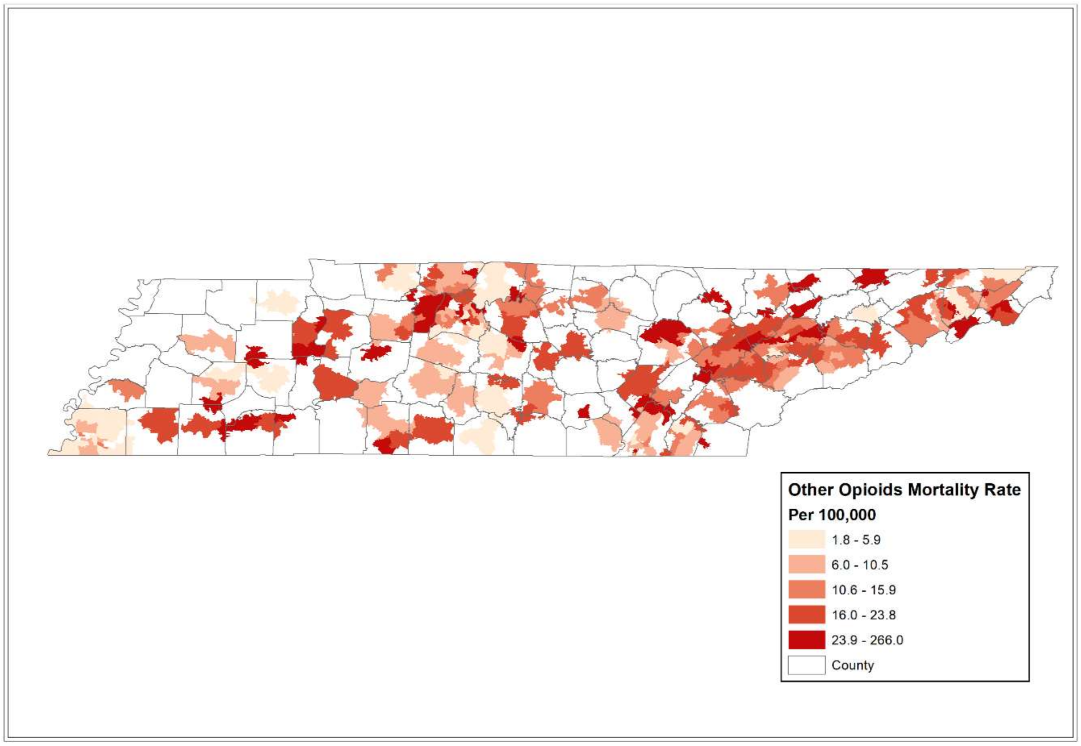

Figure 37. Tennessee Mortality with Other Opioids Related Cause of Death Rate Per 100,000 by ZIP Code, 2017

Other synthetic narcotics related mortality seemed to be clustered more randomly. See Figure 38. These clusters were found in both urban and rural areas. The clustering was similar to that which was seen from hospital discharge related to other synthetic narcotics. These clusters could have indicated areas where synthetic narcotics were used to adulterate illicit drugs. The clusters, in both urban and rural areas, could have been because synthetic opioids such as fentanyl can be used to adulterate both heroin and counterfeit prescription opioids.

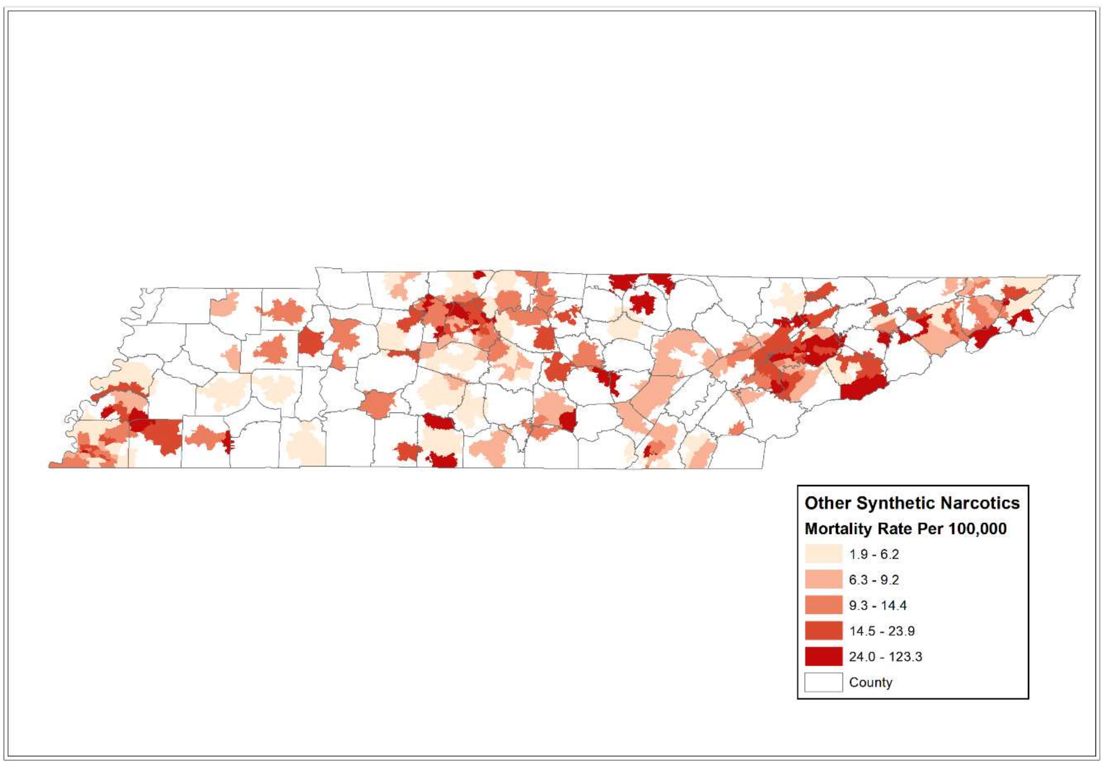

Figure 38. Tennessee Mortality with Other Synthetic Narcotics Related Cause of Death Rate Per 100,000 by ZIP Code, 2017

ANOVA of Mean Rates by ZIP Code's Associated LifeMode

ANOVA analysis was conducted based on ESRI Tapestry classifications of the ZIP codes. Initial analysis was done using Tapestry segmentations, of which there are 67 classifications. No significance was found between the means of the discharge and mortality rates among the Tapestry segmentations. This was potentially due to the fact of the large number of segmentation and similarities between the populations of these segmentations. As an alternative, ESRI LifeMode groupings were used to classify the ZIP codes. ESRI groups segmentations into 14 LifesMode that represent similar types of lifestyles. This taxonomy was used as an alternative classification scheme for ANOVA, and statistical significance was found between LifeMode groups.

Table 34 presents the p-values of the hospital discharge and mortality rates for the three classes of opioid drugs. Statistical significance was found between the mean hospital discharge rate among LifeMode groups for all three drug classifications (Heroin = 0.0001, Other Opioids = 0.0001, Other Synthetic Narcotics = 0.037). Other Opioids was the only opioid drug classification that demonstrated statistical significance among the LifeMode group's mean mortality rate (0.0001).

Table 34. Statistical Significance of Variance of Rates Among LifeModes at the ZIP Code Level

	Hospital Discharges	**Mortality**
Heroin	0.0001	0.332
Other Opioids	0.0001	0.001
Other Synthetic Narcotics	0.037	0.133

Descriptive Statistics of Hospital Discharge (Heroin, Other Opioids, and Other Synthetic Narcotics)

Descriptive statistics were created to determine the LifeModes with the highest mean hospital discharge rates. Table 35 shows the LifeModes that had the highest mean rates of heroin related hospital discharges. GenXurban, Uptown Individuals, and Midtown Singles seemed to fit into the notion that heroin hospital discharges were located in urban environment. GenXurban, as the name implies, tended to be middle-aged and urban/suburban, while Midtown Singles tended to be younger millennials and urban as well. Uptown Individuals were characterized as urban, single, and more affluent. The Family Landscapes LifeMode was associated with family-oriented segmentations. This LifeMode was somewhat unexpected but may be related to drug use by younger members of the family.

Table 35. Descriptive Statistics of LifeModes with High Average Heroin Hospital Discharge Rates by ZIP Code

n	Average Rate	LifeMode Group	Segmentations
4	437.9	Senior Styles	Silver & Gold, Golden Years, The Elders, Senior Escapes, Retirement Communities, Social Security Set
20	74.3	GenXurban	Comfortable Empty Nesters, In Style, Parks and Rec, Rustbelt Traditions, Midlife Constants
4	64.4	Uptown Individuals	Laptops and Lattes, Metro Renters, Trendsetters
14	61.8	Midtown Singles	City Strivers, Young and Restless, Metro Fusion, Set to Impress, City Commons
21	60.1	Family Landscapes	Soccer, Moms, Home Improvement, Middleburg

There was some concern by the authors that these LifeModes may not have been represented completely in the data, and the small numbers with outliers may have been driving certain mean rates up for certain LifeModes. For example, Senior Styles had a surprisingly high mean rate (437.9). LifeModes were investigated further by ZIP codes. A list of all the LifeMode groups with counts and percentages of total ZIP codes was created to verify the small numbers were not creating larger impacts on the results. See Table 36. There were four ZIP codes with the LifeMode Senior Styles represented in the data for heroin related hospital discharges. Upon further investigation, three of these Senior Styles ZIP codes were in urban areas of the state: 38105 (Memphis), 37213 (Nashville), and 37402 (Chattanooga). The ZIP code in downtown Memphis was the location of the area's largest homeless housing, medical center, and indigent public housing. The ZIP code in Nashville had a low residential population, which artificially raised the discharge rate. Chattanooga's ZIP code associated with Senior Styles was also in the city's downtown area.

Table 36. Count of Tennessee LifeModes by ZIP Code

LifeMode	Count of TN ZIPS	Percent
Rustic Outposts	332	54.7%
Cozy Country Living	91	15.0%
Hometown	39	6.4%
Family Landscapes	27	4.4%
GenXurban	24	4.0%
Middle Ground	21	3.5%
Affluent Estates	20	3.3%
Midtown Singles	16	2.6%
Ethnic Enclaves	11	1.8%
Scholars and Patriots	9	1.5%
Senior Styles	9	1.5%
Uptown Individuals	6	1.0%
Upscale Avenues	2	0.3%
Total	**607**	**100.0%**

Some of the same LifeModes were present in the four highest average other opioids hospital discharge rates. See Table 37. The LifeModes in common were Senior Styles and Uptown Individuals. Senior Styles had more ZIP codes associated with other opioids than with heroin (6, 4). Three of these ZIP codes were in common between heroin and other opioids (38105, 37402, 37774). ZIP code 37774 was in a suburban area of Knoxville. The remainder of the ZIP codes associated with Senior Styles were rural. All of the ZIP codes associated with Uptown Individuals were located in the Memphis and Nashville downtown areas (38103, 37203, 37212).

Table 37. Descriptive Statistics of LifeModes with High Average Other Opioids Hospital Discharge Rates by ZIP Code

n	Average Rate	LifeMode Group	Segmentations
67	61.0	Cozy Country Living	Green Acres, Salt of the Earth, The Great Outdoors, Prairie Living, Rural Resort Dwellers, Heartland Communities
6	60.6	Senior Styles	Silver & Gold, Golden Years, The Elders, Senior Escapes, Retirement Communities, Social Security Set
208	59.6	Rustic Outposts	Southern Satellites, Rooted Rural, Diners & Miners, Down the Road, Rural Bypasses
3	46.1	Uptown Individuals	Laptops and Lattes, Metro Renters, Trendsetters

The LifeModes Cozy Country Living and Rustic Outposts had high average hospital discharge rates for other opioids but not for heroin. These LifeModes were associated with older individuals residing in rural settings. This demonstrated how other opioids were more present in rural environments as opposed to heroin. Figure 39 shows the locations of ZIP codes associated with Country Cozy Living and Rustic Outposts. The urban centers such as those around Nashville, Memphis, Knoxville, Chattanooga, and Kingsport did not include these Life Modes.

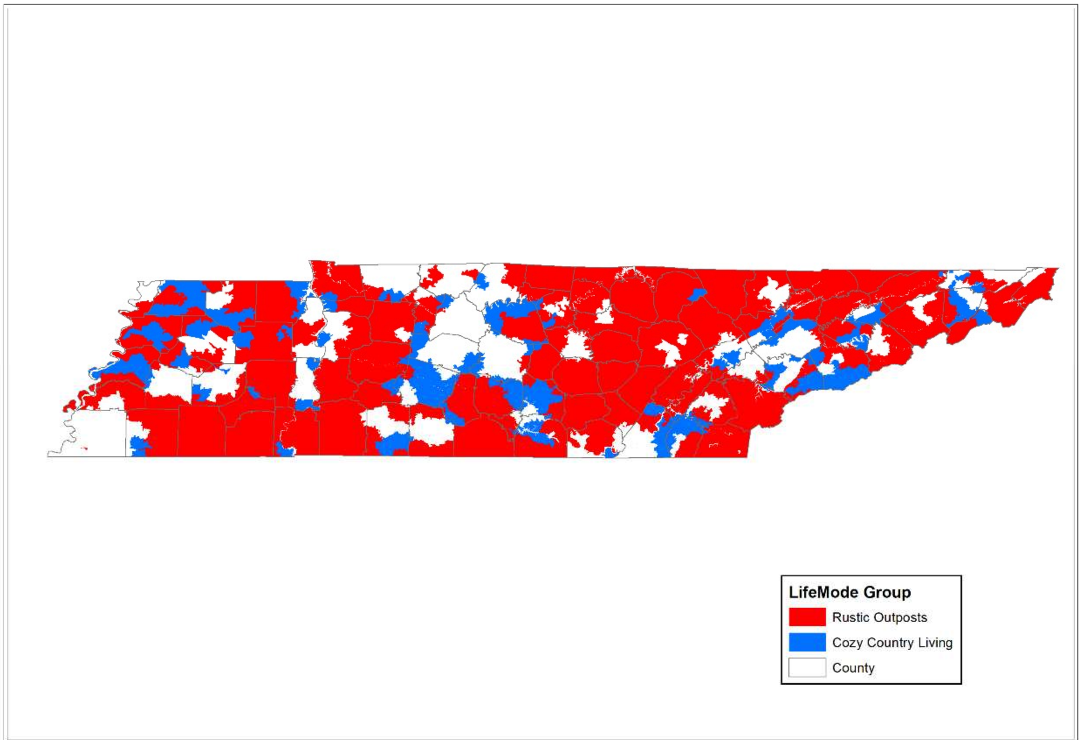

Figure 39. Tennessee ZIP Codes Associated with the ESRI LifeMode Groups Rustic Outpost and Country Cozy Living

The LifeModes with the four highest average hospital discharge rates for other synthetic narcotics represented both urban and rural ZIP codes. See Table 38. Rustic Outposts and Cozy Living were both rural LifeModes. Of the two ZIP codes associated with Senior Styles, one was an urban ZIP code in downtown Memphis (38105) and the other a rural ZIP code in Benton County (38221). The LifeMode Uptown Individuals was located in downtown Nashville (37201). This supported the idea found by rate mapping which suggests that other synthetic narcotics were in both urban and rural areas due to their use as an adulterant in both illicit heroin and counterfeit narcotics.

Table 38. Descriptive Statistics of LifeModes with High Average Other Synthetic Narcotics Hospital Discharge Rates by ZIP Code

n	Average Rate	LifeMode Group	Segmentations
1	128.7	Uptown Individuals	Laptops and Lattes, Metro Renters, Trendsetters
84	34.1	Rustic Outposts	Southern Satellites, Rooted Rural, Diners & Miners, Down the Road, Rural Bypasses
2	23.2	Senior Styles	Silver & Gold, Golden Years, The Elders, Senior Escapes, Retirement Communities, Social Security Set
31	20.5	Cozy Country Living	Green Acres, Salt of the Earth, The Great Outdoors, Prairie Living, Rural Resort Dwellers, Heartland Communities

Rules Based Association Data Mining of Hospital Discharges (Heroin, Other Opioids, and Other Synthetic Narcotics)

Spatial rules based association data mining of the hospital discharge data was conducted in addition to rate mapping, ANOVA, and descriptive analysis for each drug classification. This analysis required converting hospital discharge rates into nominal values. These nominal values for each drug can be seen in Table 39.

Table 39. Nominal Classification of Tennessee ZIP Code Discharge Rates

	Quantile				
	L	LM	M	MH	H
Heroin	2.6-13.9	14.0-30.7	30.8-50.1	50.2-80.2	80.3-2381.0
Other Opioids	3.5-21.3	21.4-32.2	32.3-48.7	48.8-73.5	73.6-245.7
Other Synthetic Narcotics	1.8-5.3	5.4-8.8	8.9-14.7	14.8-24.1	24.2-540.5

The results of the data mining for hospital discharges relating to heroin can be seen in Table 40. The data mining identified two of the same LifeModes as the descriptive analysis, Uptown Individuals and GenXurban. Both of the rules identified in the results had a consequent of high. The two ZIP codes in the dataset that had a high quantile and the LifeMode Uptown Individual were urban in the downtowns of Memphis and Nashville (37203, 38103). Sixteen of the twenty records in the dataset had a consequent quantile value of high and the LifeMode GenXurban. The results supported the findings of the rate mapping and descriptive statistics that heroin was abused in more urban and suburban areas.

Table 40. Rules of Interest Between LifeMode and Heroin Hospital Discharge Quantile

Consequent	**Antecedent**	**Instances**	**Support %**	**Confidence %**	**Lift**
High	Uptown Individuals	4	1.5	50	2.5
High	GenXurban	20	7.5	40	2.0

Only one rule was identified by the data mining, and it had a low quantile consequent. Affluent Estates was a LifeMode identified as having low levels of other opioids mortality. See Table 41. This LifeMode group was associated with being affluent. Some of the segmentations within this group are associated with suburbia such as BoomBurbs, Savvy Suburbanites, and Exurbanites. These segmentations suggested a reduction in the level of other opioids abuse in suburban areas compared to rural.

Table 41. Rules of Interestingness Between LifeMode and Other Opioids Hospital Discharge Quantile

Consequent	**Antecedent**	**Instances**	**Support %**	**Confidence %**	**Lift**
Low	Affluent Estates	19	4.3	63.2	3.2

Similar results were found in the data mining of hospital discharge rates related to other synthetic narcotics. See Table 42. All of the rules had low quantile values as consequents. Affluent Estates was identified as having low rates of heroin related hospital discharge as was the LifeMode Ethnic Enclaves, which was associated with Hispanics.

Table 42. Rules of Interest Between LifeMode and Other Synthetic Narcotics Hospital Discharge Quantile

Consequent	Antecedent	Instances	Support %	Confidence %	Lift
Low	Affluent Estates	10	4.5	70.0	3.5
Low	Ethnic Enclaves	9	4.1	66.7	3.3

Descriptive Statistics of Mortality (Other Opioids)

The ANOVA analysis in Table 34 indicated that there was only a statistical difference between the mean mortality rates of the ZIP code based on LifeMode for other opioids mortalities. The descriptive statistics of the highest four average rates can be seen in Table 43. Uptown Individuals, Rustic Outposts, and Senior Styles were identified in the descriptive analysis of both the mortality and hospital discharge rates. Both of the ZIP codes associated with Uptown Individuals were located in Downtown Nashville (37201, 37203). All the ZIP codes associated with Senior Styles were in rural or suburban areas of the state (38341, 38558, 37774). The LifeMode Scholars and Patriots was identified as being associated with mortality but not hospital discharge associated with other opioids. This LifeMode was associated with individuals living in areas around universities or military bases. The four ZIP codes identified were all near or contain public universities (37130, 37902, 37920, 38501). This could suggest that college-aged individuals have less access to health care so they do not seek emergency care during an overdose, but they still are at risk of abusing these drugs.

Table 43. Descriptive Statistics of LifeModes with High Average Other Opioids Mortality Rates by ZIP Code

n	Average Rate	LifeMode Group	Segmentations
2	39.8	Uptown Individuals	Laptops and Lattes, Metro Renters, Trendsetters
4	32.6	Scholars and Patriots	Military Proximity, College Towns, Dorms to Diplomas
73	29.9	Rustic Outposts	Southern Satellites, Rooted Rural, Diners & Miners, Down the Road, Rural Bypasses
3	25.4	Senior Styles	Silver & Gold, Golden Years, The Elders, Senior Escapes, Retirement Communities, Social Security Set

Rules Based Association Data Mining of Mortality (Other Opioids)

The quantile values for the mortality rates that were used in the spatial rules association data mining of other opioids related mortality can be seen in Table 44.

Table 44. Nominal Classification of Tennessee ZIP Code Mortality Rate

	Quantile				
	L	**LM**	**M**	**MH**	**H**
Other Opioids	1.8-5.9	6.0-10.5	10.6-15.9	16.0-23.8	23.9-266.0

The results of the spatial rules based data mining of other opioids mortality rates can be seen in Table 45. The data mining only returned rules with low consequent quantile values similar to the results for other opioids and other synthetic narcotics hospital discharges. Similarly, the results showed an association between low other opioids mortality and low heroin and other opioids related hospital discharges between the LifeMode groups Ethnic Enclaves and Affluent Estates. The results also showed a low association between Family Landscapes and Midtown Singles and low other opioids mortality. Interestingly, these LifeModes were found to be associated with high heroin hospital discharges in the descriptive analysis.

Table 45. Rules of Interest Between LifeMode and Other Opioids Mortality Quantile

Consequent	Antecedent	Instances	Support %	Confidence %	Lift
Low	Ethnic Enclaves	9	4.0	77.8	3.9
Low	Affluent Estates	13	5.8	53.8	2.7
Low	Midtown Singles	13	5.8	46.2	2.3
Low	Family Landscapes	15	6.7	40.0	2.0

Descriptive Statistics of United States Mortality (Heroin, Other Opioids, and Other Synthetic Narcotics)

Analysis of mortality was done at the smaller geographic scale of the United States at the county level. This was done to compare the findings of the larger geographic scale analysis done at the Tennessee ZIP code level. This analysis relied solely on mortality data from the CDC since a national set of hospital discharge data was not available. First, an ANOVA analysis was done on the mean mortality rates for each opioid drug class based on the counties' LifeMode group. The p-values from this analysis can be seen in Table 46. It was found that there was a statistically significant difference in the mean mortality rate for each county among LifeMode groups.

Table 46. Statistical Significance of Variance of Rates Among LifeModes at the United States County Level

	Mortality
Heroin	0.0001
Other Opioids	0.0001
Other Synthetic Narcotics	0.0001

A descriptive analysis of the mean rates was done for each of the drug classifications to determine LifeModes that were associated with higher mortality. The results of the descriptive analysis can be seen in Table 47. The descriptive analysis found that GenXurban and Senior Styles were the only LifeModes in common between the national mortality rate and state level heroin discharge rate. GenXurban was associated with urban counties, which supported the notion of heroin being a drug available in urban settings. Senior Styles was identified in the heroin hospital discharges as well as some of the previous opioid rate analyses. This is surprising since heroin has typically been associated with youth abuse. Further examination found that these identified counties tended to be areas with LifeModes associated with retirement, near the ocean coast, and also near urban centers. The five counties identified were: Ocean County, NJ; Cape May County, NJ; Palm Beach County, FL; Collier County, FL; and Lee County, Florida. All of these counties were on the East or Gulf Coast.

Table 47. Descriptive Statistics of LifeModes with High Average Heroin Mortality Rates by United States County

n	Average Rate	LifeMode Group	Segmentations
16	13.2	Hometown	Family Foundations, Traditional Living, Small Town Simplicity, Modest Income Homes
16	12.5	Cozy Country Living	Green Acres, Salt of the Earth, The Great Outdoors, Prairie Living, Rural Resort Dwellers, Heartland Communities
37	12.1	GenXurban	Comfortable Empty Nesters, In Style, Parks and Rec, Rustbelt Traditions, Midlife Constants
5	11.3	Senior Styles	Silver & Gold, Golden Years, The Elders, Senior Escapes, Retirement Communities, Social Security Set

Similar LifeModes were identified with the descriptive analysis of the other opioids mortalities at the United States county level and Tennessee hospital discharge and mortality rates. See Table 48. Rustic Outposts was one of the LifeModes identified at the county level that was also identified in the Tennessee ZIP code analysis of hospital discharges and mortality. There were only three counties identified associated with Rustic Outposts, but larger numbers of ZIP codes were identified in the analysis of discharge (208) and mortality (73) rates. Rustic Outposts was the most common LifeMode at the ZIP code level in Tennessee (332). The identified counties associated with Rustic Outposts were located in rural South Carolina and Texas.

Cozy County Living was another identified LifeMode that was rural. The identification of GenXurban and Hometown supported previous findings with the same data that show other opioids mortality occurring across the urban/suburban continuum.

Table 48. Descriptive Statistics of LifeModes with High Average Other Opioids Mortality Rates by United States County

n	**Average Rate**	**LifeMode Group**	**Segmentations**
9	12.0	Cozy Country Living	Green Acres, Salt of the Earth, The Great Outdoors, Prairie Living, Rural Resort Dwellers, Heartland Communities
19	8.6	Hometown	Family Foundations, Traditional Living, Small Town Simplicity, Modest Income Homes
3	8.4	Rustic Outposts	Southern Satellites, Rooted Rural, Diners & Miners, Down the Road, Rural Bypasses
27	6.9	GenXurban	Comfortable Empty Nesters, In Style, Parks and Rec, Rustbelt Traditions, Midlife Constants

The results of the descriptive analysis of means of county level other synthetic narcotics mortality can be seen in Table 49. These results were similar to the analysis of Tennessee hospital discharges in that both included Cozy Country Living, Rustic Outposts, and GenXurban. The LifeModes also represented segmentation associated with both urban and rural environments. This was found in the ZIP code level analyses of other synthetic opioids rates and further supports the idea that this drug is found in both types of locations due to its use as an adulterant in multiple types of illicit opioids.

Table 49. Descriptive Statistics of LifeModes with High Average Other Synthetic Narcotics Mortality Rates by United States County

n	Average Rate	LifeMode Group	Segmentations
55	28.7	Cozy Country Living	Green Acres, Salt of the Earth, The Great Outdoors, Prairie Living, Rural Resort Dwellers, Heartland Communities
22	27.4	Hometown	Family Foundations, Traditional Living, Small Town Simplicity, Modest Income Homes
16	26.7	Rustic Outposts	Southern Satellites, Rooted Rural, Diners & Miners, Down the Road, Rural Bypasses
56	22.6	GenXurban	Comfortable Empty Nesters, In Style, Parks and Rec, Rustbelt Traditions, Midlife Constants

Rules Based Association Data Mining of United States Mortality (Heroin, Other Opioids, and Other Synthetic Narcotics)

The results of the association data mining for heroin mortality can be seen in Table 50. Two rules of interest were identified, one with a high consequent value associated with Senior Styles and one with a low consequent associated with Ethnic Enclaves. Senior Styles was identified in the descriptive analysis of heroin mortality at the U.S. county level and the Tennessee ZIP code level as well.

Table 50. Rules of Interest Between LifeMode and Heroin Mortality Quantile at the United States County Level

Consequent	Antecedent	Instances	Support %	Confidence %	Lift
High	Senior Styles	5	2.8	40.0	2.0
Low	Ethnic Enclaves	20	11.0	70.0	3.4

The data mining for other opioids mortality identified four rules with two high and low consequents seen in Table 51. The LifeMode Rustic Outposts was identified as being associated with high other opioids mortality in both the data mining and the descriptive analysis. Rustic Outposts was also identified in the descriptive analysis of other opioids mortality at the Tennessee level but not Cozy Country Living. Ethnic Enclaves was also identified as associated with low other opioids mortality in the Tennessee data mining analysis.

Table 51. Rules of Interest Between LifeMode and Other Opioids Mortality Quantile at the United States County Level

Consequent	Antecedent	Instances	Support %	Confidence %	Lift
High	Rustic Outposts	3	2.0	66.7	3.8
High	Cozy Country Living	9	6.1	66.7	3.8
Low	Uptown Individuals	8	5.4	62.5	2.9
Low	Ethnic Enclaves	19	12.9	47.4	2.2

All of the rules in the data mining of other synthetic narcotics mortalities had low consequent quantile values. See Table 52. Three LifeMode groups were identified Uptown Individuals, Ethnic Enclaves, and Next Wave. All of these LifeModes were either related to more affluent or urban populations or recent immigrants. Analysis of other synthetic narcotics Tennessee discharge rates identified LifeModes associated with both urban and rural high mortality. However, the results of this analysis identified urban LifeModes that are least likely to be impacted by other synthetic narcotics mortality.

Table 52. Rules of Interest Between LifeMode and Other Synthetic Narcotics Mortality Quantile at the United States County Level

Consequent	Antecedent	Instances	Support %	Confidence %	Lift
Low	Uptown Individuals	9	3.1	66.7	3.3
Low	Ethnic Enclaves	15	5.1	66.7	3.3
Low	Next Wave	5	1.7	40.0	2.0

Discussion

Rate mapping provided initial clues to the nature of opioid abuse in the state of Tennessee. Both the hospital discharge and mortality rates relating to heroin showed a spatial relationship between urban centers and urban peripheries to heroin. Hospital discharge rates related to other opioids were present in both urban and rural settings but seemed to have higher rates in rural areas. This same pattern of other opioids mortality being in both urban and rural areas was found in Middle and East Tennessee. However, less other opioids mortality was seen in West Tennessee, only 19.1 percent of ZIP codes with other opioids mortality. The mortality that was seen in West Tennessee was exclusively rural and near Middle Tennessee.

The rate mapping of both hospital discharges and mortalities related to other synthetic narcotics presented a highly clustered pattern. These clusters were found in both urban and rural areas and may have been locations where synthetic narcotics were used as adulterants in illicit opioids. The fact that these clusters are both urban and rural could be related to the fact that synthetic narcotics can be used as an adulterant in both heroin and counterfeit prescription opioids.

These rate maps suggested that heroin was an urban drug. Other opioids were found in both urban and rural areas but had a stronger presence in rural locations. Other synthetic narcotics were present in both, but their presence was related to where the drugs were used as an adulterant in illicit drugs.

The investigation of the rates by ESRI Tapestry LifeMode group provides not only further insight into the location of where the drugs were abused but also the socioeconomic nature of who was abusing these drugs. By comparing the results of the data analysis at the Tennessee and national levels, it was possible to identify some of the scale dependencies of opioid abuse. For example, the analysis of hospital discharge data at the state level largely found that heroin use was exclusively associated with urban LifeModes (GenXurban, Uptown Individuals, Midtown Singles, Senior Styles). However, analysis of mortality at the national level identified counties associated with rural and suburban LifeModes as well (Cozy Country Living, Hometown).

The analysis of other opioids rates offered further examples of scale dependency. Senior Styles was identified as being associated with high other opioids hospital discharge and mortality rates at the state level but not the national. Similarly, the LifeMode Uptown Individuals showed an association with high other opioids related hospital discharge and mortality rates. However, at the national level it was found to be associated with low other opioids mortality in the rules based association data mining analysis. Likewise, the LifeMode Uptown Individuals was also found to be associated with high other synthetic narcotics hospital discharge rates in Tennessee but low mortality in the data mining of national other synthetic narcotics mortality. These examples demonstrated the scale dependent aspect of opioid misuse. In other words, LifeModes that misused opioids in Tennessee at the ZIP code level may not have at the county level across the country, and vice versa.

The analysis of other opioids mortality rates also identified LifeModes that may have been scale dependent. Scholars and Patriots was found to be associated with higher other opioids mortality. This was not found at the national level, but this may have had to do with the scale of the analysis. This association may have only been identifiable at the larger geographic scale, ZIP code in this case, due to the small area of influence around college campuses and military bases. This may not have been observable at the county level.

Somewhat similarly, the LifeMode Hometown was identified with a high rate of mortality for all drug classes at the national level. However, it was not identified with any analysis at the Tennessee state level while still being the third most common LifeMode among the state's ZIP codes. This was another example of scale dependency in which the LifeMode Hometown was not associated with opioid use in the state of Tennessee at the ZIP code level but was at the county level across the country.

The spatial rules based association data mining confirmed findings of the descriptive analysis but also identified LifeModes associated with low mortality. One LifeMode consistently associated with low mortality was Ethnic Enclaves. Ethnic Enclaves was a LifeMode group of Tapestry segmentations associated with Hispanic populations. Also, the LifeMode Affluent Estates was found to be consistently associated with low hospital discharges and mortality in the Tennessee ZIP code level analysis.

Conclusion

This research demonstrated the use of hospital discharge and mortality rates at two different geographic scales to identify differing use patterns and scale dependencies of opioid misuse among different ESRI LifeMode groups based on drug classifications. Investigation using LifeModes highlighted differences in the socioeconomic aspects of opioid misuse. Opioid mortality rates compared at the national and state levels highlighted the scale dependencies of misuse in terms of LifeMode.

While analyzing data at different scales identified scale dependency, there was also evidence of locational dependency of opioid misuse by drug type. Heroin, other opioids, and other synthetic narcotics were found in different locations across the urban/rural continuum, demonstrating the locational dependency of misuse within the state of Tennessee.

For example, evidence of heroin misuse was linked to urban locations. Heroin hospital discharges were clustered around the urban population centers of the state. However, heroin mortality was found around the fringes of urban areas. This could have been the result of a lack of access to medical attention after a heroin overdose. This would not have occurred in more rural areas where heroin was not available in the illicit drug market.

Other opioids also demonstrated locational dependency. Evidence of other opioids misuse was found in both urban and rural areas. However, this was not seen consistently across the state. Middle and East Tennessee were the locations of 80.9 percent of the ZIP codes with other opioids related mortality. This may be an indication of differences in the populations that lead to locational dependency of other opioids misuse. West Tennessee has a larger population of African Americans than does the rest of the state. This could have resulted in fewer other opioids mortalities due to African Americans having less access to medical care and being subject to prescribing biases of medical professionals (Alexander et al., 2018; Lopez, 2016).

The locational dependency of other synthetic narcotics seemed to be more related to potential areas where synthetic narcotics were used as an adulterant in illicit drugs. Hospital discharges and mortality relating to other synthetic narcotics were clustered in both urban and rural areas. This may be because synthetic narcotics such as fentanyl were used in both heroin, an urban drug, and counterfeit prescription opioids, more rural drug (CDC, 2018a; Ciccarone, 2017a). Location dependency in the case of other synthetic narcotics hospital discharges and mortality was based more on where drugs were used as adulterants regardless of urban or ruralness of an area.

Future research should build upon these findings. Understanding the LifeMode and Tapestry segmentation associated with particular drugs can be used to conduct more focused drug abuse interventions. This research did not use Tapestry segmentation due to a lack of significance between means. Using other datasets with more available data at different scales may be beneficial. These data sources such as electronic health records or Narcan distribution could be collected at the ZIP code scale. This may allow for more full leverage of ESRI Tapestry or other geodemographic segmentation.

Additionally, future research should account for the small sample size of ZIP codes with certain LifeModes. In some cases, there were as few as one or four ZIP codes represented in this data. ANOVA is a non-parametric test and requires a minimum sample size of 30. Data from additional states or individual level data should be used to overcome this limitation.

Finally, the segmentations that make up LifeModes should be further investigated. This could perhaps be done with hierarchical modeling techniques. The interactions and relationships of different segmentations within LifeModes should be investigated. Geodemographic segmentation systems are a tool that presents promise toward creating more efficient and focused health interventions. These data combined with new technology could provide new opportunities to address the problems presented by current and future drug epidemics.

List of Abbreviations

Analysis of Variance (ANOVA), Centers for Disease Control (CDC), Environmental Systems Research Institute (ESRI), International Statistical Classification of Diseases and Related Health Problems 10th Edition (ICD-10), Topologically Integrated Geographic Encoding and Referencing (TIGER), Zone Improvement Plan (ZIP)

Chapter 6 Conclusions

This study was done in four parts and focused on the spatial and demographic aspects of the American opioid epidemic. Geodemographic segmentation systems were explored as a socioeconomic variable to improve intervention, prevention, and treatment of opioid drug abuse. Chapter 2 used data from the CDC to investigate the demographics of the opioid epidemic. The findings challenged the notion that the epidemic was predominately associated with white, middle-aged, rural males. This notion failed to consider the different classes of opioid drugs, historical development, and the latest research into the opioid epidemic. Considering opioid drugs by the ICD-10 classification offered a different perspective on the epidemic. Heroin was found to be more predominant in urban areas, whereas other opioids abuse was highest in rural and suburban areas but was still present in urban areas. Other synthetic narcotics abuse was found in areas where synthetic opioids had been used as an adulterant in illicit drugs.

The opioid drug epidemic developed overtime beginning with prescription opioid abuse, which was followed by an increase in heroin use and most recently an increase in synthetic opioids. This is not represented in the notion of the opioid crisis being limited to white, middle-aged, rural males. It also fails to account for recent research which indicates opioid abuse is increasing faster among women and African Americans. This would have an impact on treatment, intervention, and prevention related to the epidemic.

Geodemographics segmentation systems were used as a socioeconomic variable in the third and fourth chapters in the paper. Chapter 3 of the paper was a literature review of previous research using GS systems in health care related areas. The review found that much of the previous research had been conducted in the United Kingdom, with limited research taking place in the United States. The papers fell into one of five categories relating to the use of GS systems: as an alternative measure of deprivation, as a measure of deprivation, used for identifying populations at risk, used in health care outreach, and used to improve spatial analysis. The papers demonstrated how GS systems could improve research, intervention, prevention, and treatment in these research areas.

Chapter 4 used ESRI Tapestry segmentation data to analyze opioid mortality data using spatial rules based association data mining. This analysis identified Tapestry segmentations that were associated with high opioid mortality based on drug classifications. These findings were further investigated with demographic statistics from publicly available sources such as the United States Census and the CDC. This found an association between opioid mortality and higher opioid prescribing and unemployment rates and that mortality was associated with a high percentage of disabled, higher median ages, lower minorities, and lower urbanization.

The findings were also compared to a descriptive analysis of Tennessee opioid mortality data. The U.S. and Tennessee ZIP code level analysis found that county level analysis was better for rural explaining rural populations. This was due to the higher degree of heterogeneity of the population in urban areas. This suggests that using county level data may have limitations for studying drugs such as heroin, which are associated with urban areas.

The fourth chapter also demonstrated how the Tapestry segmentation identified in the analysis could be used to conduct more efficient interventions, preventions, and treatments. This was done using the ESRI Tapestry documentation, which included information about different segmentations' lifestyle preferences.

Chapter 5 furthered the investigation by using hospital discharge and mortality data at the ZIP code level from the Tennessee Department of Health. The research began by mapping opioid related hospital discharge and mortality rates at the ZIP code level. This analysis was used to identify hot spots of opioid abuse across the state. These hot spots were further investigated with ESRI Tapestry LifeMode groupings in ANOVA and descriptive analysis. This identified LifeModes that had high opioid hospital discharge and mortality rates. Spatial rules based association data mining was used to further investigate these findings.

National county level mortality data were used to investigate scale dependency between the Tennessee and United States level data. This demonstrated how analysis at different scales identified varying LifeModes. For example, the LifeModes Hometown and Cozy Country Living are two rural LifeModes that were found associated with heroin mortality at the national county level scale. Neither of these LifeModes was identified at the local ZIP code scale when analyzing the hospital discharge or mortality data.

All of the research suggested heroin was abused in urban settings. Other opioids abuse is found in both urban and rural areas, but rates are higher in rural. The location of other synthetics narcotics abuse was related to areas where the synthetic opioids had been used to adulterate illicit drugs. These drugs were abused in both urban and rural areas since they can be used to adulterate heroin and counterfeit prescription opioids.

Future studies will expand upon the research in this dissertation. This will include the use of finer level datasets and other geospatial statistical analysis. Experian Mosaic GS will be explored as an alternative to ESRI Tapestry. Mosaic enables lifestyles to be identified at the household level. This can be used to better approximate the lifestyle associated with an individual health record. These types of records could include sources such as electronic medical records and medical insurance claims. The population level analysis from this dissertation will be complemented by this type of individual level investigation and will further knowledge of how GS can improve intervention, prevention, and treatment.

The spatial analysis will be improved by other spatial statistical techniques such as hot spot, temporal hot spot, and cluster analysis. This will improve upon visually identifying hot spots and will determine the statistical validity of identified areas at risk. Including a temporal component to the analysis will help identify emerging trends of opioid misuse.

This research identified the complex variety of ways the opioid epidemic impacted communities across the United States. The investigation intended to identify ways that GS systems can be used to improve response to the opioid epidemic. It is hoped that the findings of this and future research will lead to improved responses to the current opioid and other drug epidemics.

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