Identifying Hotspots of Chronic Non-malignant Pain in Orlando, Florida

Authoring Students: Jessica Bogard and Martin Perry

AdventHealth University

Project Chair: Sarah L. Snell, DNP, CRNA

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Abstract

Chronic pain (CP) is a biopsychosocial condition and is one of the most prevalent yet underestimated diagnoses in the world. A reported 50 million people in 2016 experienced CP in the United States, and this number continues to grow exponentially in subgroup variations, such as high-impact CP, which accounts for an additional 19.6 million individuals. A more specific category of CP, chronic non-malignant pain (CNMP), affects 20% of the world's population. Collectively, CNMP has reduced quality of life, increased debilitating outcomes, and has cost the healthcare system billions of dollars every year. Though the prevalence of CP is well-established globally and nationally, the literature does not identify prevalence of more specific subsets, such as high-impact or non-malignant pain. Furthermore, there is a gap in the literature for CNMP in Orlando, Florida. Therefore, this scholarly project extrapolated existing national data of CP from the Center for Disease Control and Prevention (CDC) and, using a geographical information system (GIS), identified clusters of specific demographics related to CNMP in the Orlando community like sex, age, race, and a household income of less than 100% of the federal poverty line. Utilizing a geographic information system (GIS) we used K-means, empirical bayesian kriging (EBK), and the Getis Ord-Gi statistic to predict rates of clustering of CNMP populations within a 30-minute drive time of AdventHealth hospital main campus in Orlando, separated by census tracts. Hot spots concentrated on the northwest Apopka region due to the population having the highest risk factors for CNMP; being at or below 100% the federal poverty line and age greater than 44 years old. Such statistics can guide the development of health care strategies to appropriately address this debilitating disease and minimize health costs.

Keywords: Chronic pain, chronic non-malignant pain, high-impact chronic pain

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Chronic pain (CP) is a complex and common problem that affects the global population. It is estimated that 1.5 billion people are affected by chronic pain, and according to the World Health Organization, chronic pain is one of the most significantly underestimated health issues in the world today (Darnell, 2019; World Health Organization, 2004). In the United States specifically, an estimated 50 million Americans reported they experienced CP, with vulnerable populations, such as those who identified as living in poverty, or insured with public health coverage, suffering at a significantly higher rate (Dahlhamer et al., 2018; Dowell, Haegerich, & Chou, 2016). Of interest is the gap in published data for the state of Florida. The incidence of chronic pain is not directly addressed in publications or state data; rather, indicators, such as primary and contributing diagnosis are reported. These disorders are extrapolated from ICD-10 codes, and while chronic pain is frequently associated with many of the reported disorders, it is not clear how many individuals within the state of Florida also experience chronic pain (Florida Department of Health, 2018). This absence of data makes the appropriate allocation of health care resources problematic.

Advanced nurse education has enabled nurses to decrease the frequency of pain and improve patient satisfaction in pain control (Institute of Medicine, 2011). In fact, Certified Registered Nurse Anesthetists (CRNAs) are actively engaged in the process of improving outcomes for individuals who suffer from chronic pain. With quality improvement expertise, expansive knowledge of multi-modal pain management, and a focus on patient-centered care, CRNAs are uniquely positioned to address publication gaps and to guide the appropriate allocation of healthcare resources (American Association of Nurse Anesthetists, 2014).

However, chronic pain data and commonly associated demographics must first be clearly understood at the local level in order to target this population and properly distribute available resources.

Significance & Background of Clinical Problem

Currently, there is inconsistent management of chronic non-malignant pain (CNMP), resulting in substantial physical, emotional, and societal impacts (U.S. Department of Health and Human Services, 2019). On a macro scale, the societal burden of CNMP is vast and encompasses disability, work absenteeism, and economic impacts. From 1990 to 2010, chronic lower back pain, a common diagnosis within CNMP, has been the leading cause of disability in the U.S. population (Shmagel, Foley, & Ibrahim, 2016). Fibromyalgia, another diagnosis associated with CNMP, has a disability rate as high as 30% of those afflicted. In addition, work absenteeism in the form of sick leave occurs at a rate of 43 to 78% (Dueñas, Ojeda, Salazar, Mico, & Failde, 2016). Healthcare costs related to CNMP have also been increasing and are estimated to be $100-300 billion in the U.S. as of 2011 (CDC, 2020; Institute of Medicine, 2011; Martin et al., 2008). These large-scale issues, while resulting in significant economic impacts, are outweighed by the negative effects experienced by those diagnosed with CNMP.

On a micro-scale, CNMP affects the individual physically, psychologically, and emotionally. There is a negative correlation between CNMP and physical aptitude that includes the inability to perform activities of daily living, walking, and maintaining an independent lifestyle (Dueñas et al., 2016). Moreover, as pain intensifies, its associated side effects increase. These include a deterioration of physical and cognitive abilities and the development of sleep disturbances. The interplay between CNMP and sleep disturbance further results in elevated stress, anxiety, depression, and higher pain intensity (Dueñas et al., 2016). Additionally, feelings of irritability and anger are projected onto family members, negatively affecting interpersonal relationships and increasing isolation. This creates a vicious cycle exacerbating the condition and considerably impairing quality of life.

In regards to quality of life, CNMP is negatively linked to increased rates of suicide and disability among those reporting CNMP (Calati, Bakhiyi, Artero, Ilgen, & Courtet, 2015; Racine, 2018). According to Cheatle (2016), 50% of those who have CNMP have some form of depression, and 18-50% have experienced suicidal ideation.

The opioid epidemic has plagued the nation as opioids have become a generalized treatment for CNMP regardless of pain origin (CDC, 2020), and there is a strong relationship between depression and CNMP patients treated with long-term opioids (Valkanoff et al., 2012; Yasaei, Peterson, & Saadabadi, 2021). If there is no clear understanding of prevalence and treatment differences between CP and CNMP, there can be an over-prescribing of opioids, which has proven to be effective with chronic malignant pain but is ineffective for the management of CNMP, which leads to addiction and its negative impacts (Meuser et al., 2001; Yasaei et al., 2021). The issue of CNMP management has been a hotly debated topic within Florida as it has been a battleground for pain clinic regulation and mandated prescription drug monitoring programs (CDC, 2019). Subsequently, opioid prescriptions have decreased in 80% of Florida counties from 2010 to 2015, which has led to a decrease in prescription opioid-related overdose deaths (CDC, 2019). However, illicit opioid and synthetic analog-related deaths increased by 5.9% from 2016 to 2017 in Florida, resulting in more than 28,400 overdose deaths (CDC, 2019). While pill mills have been largely shut down, illegal drug usage has increased. It has been suggested, on a national level, that a relationship exists between an increase in illicit opioid use and the implementation of more stringent narcotic prescription regulation without the concurrent availability of other treatment modalities (U.S. Department of Health and Human Services, 2019).

Health care facilities find it challenging, however, to appropriately allocate resources for CNMP management without a clear understanding of the current burden of, specifically CNMP within the state of Florida. There exists a need, therefore, to more clearly quantify this public health problem. The purpose, therefore, of this scholarly project was to employ a geographical information system (GIS) to identify clusters of specific demographics related to CNMP within the Orlando community to assist with local decision making regarding the appropriate allocation of healthcare resources and the development of strategies to address this debilitating disease.

Scholarly Project Definitions and Nomenclatures

To properly frame the discussion of CNMP, it is essential to understand that many nomenclatures for chronic pain exist which result from the consideration of pain severity, duration, and its impact on activities of daily living (Dahlhamer et al., 2018; Korff et al., 2016; Pitcher, Von Korff, Bushnell, & Porter, 2019). The term chronic pain traditionally is described as pain that lasts for more than three months, while acute pain lasts for less than three months. Additional subsets of chronic pain, however, include chronic malignant pain, chronic non-malignant pain, and high-impact chronic pain. The most recent literature highlights high-impact chronic pain, which is described as pain that limits self-care and ability to maintain work and social life (Dahlhamer et al., 2018; Pitcher et al., 2019). Dahlhamer et al. (2018) specifically uses the generalized term "chronic pain" (Mathieson et al., 2020). A 2016 pilot study, however, states explicitly that cancer pain was not included in Dahlhamer's study (Korff et al., 2016). Therefore, clarity is needed when performing research as to the foundational operational definitions. It is also important to recognize that disparities in defining chronic pain have resulted in misdiagnosis as well as incorrect treatment (Dansie & Turk, 2013), further supporting the need for a standardized definition. Thus the definition of CNMP for this scholarly project will be pain lasting longer than three months of a non-cancerous origin.

PICOT Evidence Review Questions

The first question addresses the clinical problem: In adults (P), what are the demographics in Orlando, Florida (I) compared to the national level (C) for CNMP (O)? The second question addresses the clinical innovation: In adults living in Orlando, Florida (P), does the employment of GIS cluster analysis (I) result in the identification of CNMP census tracts that can guide AdventHealth healthcare strategies and inform resource allocation decision making (O)?

Search Strategy/Results

The search strategy included the following databases, governmental agencies, and professional practice organizations: PubMed, CINAHL, Cochrane Review, CDC, and Google Scholar. A total of 691 articles were initially retrieved. Fifteen articles met inclusion criteria, including chronic non-malignant pain, national, Florida, incidence, demographics, and prevalence. Exclusion criteria were research articles not written in English. Key Search Terms and MESH combinations included: *Chronic Pain* AND *prevalence,* OR *incidence,* AND *Florida,* OR *United States,* AND *Non- malignant,* OR *non-cancer,* AND *low back pain* AND *fibromyalgia,* AND *epidemiology OR demographics.* MESH terms included: *Chronic pain, epidemiology, incidence, risk factors, numerical data, statistics, demography, prevalence, and United States.* The search limits were: English language, human subjects, and research articles.

GRADE

The GRADE criteria were used in rating the combined level of evidence for the prevalence and demographics of CNMP in the nation compared to Florida. There were three studies found that include findings of Florida's CP prevalence or demographics (Chronic Conditions Data Warehouse, 2018; Health Council of South Florida, 2013; Snell, Hughes, Lukman, & Norman, 2019). The GRADE started at four. Limitations in study design caused us to grade down by one the quality of evidence. Problems associated with methodological flaws include the lack of standardized definitions of CP across studies. This is an issue due to different definitions possibly leaving out multiple patients that would have qualified under a standard. Indirectness across studies caused us to GRADE down the evidence by one due to population exclusion being found across varying studies. Frequently, different age groups and institutionalized populations were excluded, which could have skewed the data. Recall bias was also prominent in multiple studies due to the self-reporting of pain within surveys. Due to these studies being strictly surveys, there was frequently a lack of confirmation of results, specifically with a medical diagnosis to cross-reference each participant's answer. Inconsistencies were also found within studies as many systematic reviews had a wide variety of populations that they compared. The studies displayed indirectness due to the sample sizes' varying age group limits. Overall, the quality of the evidence is low, with a GRADE level of two. We recommend further investigation into the prevalence of CNMP amongst the Floridian population to fill in the gap in the literature, specifically related to demographics, to identify the population’s characteristics.

Literature Review and Synthesis Review of Evidence

Chronic non-malignant pain (CNMP) can negatively affect quality of life and consequently become a debilitating disease. Understanding the demographics of CNMP is key to identifying patient populations that are at higher risk. Currently, the location of patient populations with CNMP is unknown in Orlando, Florida. Through the use of geospatial analysis, populations at a high risk of CNMP can be identified as previous population studies have been successful using this method (Chang, Pearson, & Owusu-Edusei, 2017; Geraghty et al., 2010; Iloglu et al., 2021; Stopka, Krawczyk, Gradziel, & Geraghty, 2014; Zhang & Tripathi, 2018;). By using geospatial analyses, local hospitals can comprehend what the patient's specific needs are for a given census tract. For example, one hospital division may have more CNMP hot spots and emergency room admissions than another. By identifying where the clusters are, hospitals can better allocate the resources needed in order to direct optimal care.

Geographic Concepts of Geospatial Analysis

To employ geospatial analysis, foundational concepts regarding geography must first be understood. One of the primary tenants upon which the study of geography is based was first described by Waldo Tobler as ‘everything is related to everything else but near things are more related than distant things' (Foresman & Luscombe, 2017; Klippel et.al., 2011; Miller, 2004). This statement is known as the first law of geography. While this principle appears reasonably basic, the understanding that entities that are near are more likely to interact and develop relationships and as things move further apart relationships, begin to decline with increasing distance is foundational to geospatial science. Based on this concept, it is possible to mathematically analyze those spatial relationships (Klippel et al., 2011; Miller, 2004). The second law of geography delineates that 'things that know where they are can act on their locational knowledge. Spatially enabled things have increased financial and functional utility' (Foresman & Luscombe, 2017). This financial and functional utility is increasingly pertinent to healthcare systems as they are financial entities. According to this law, agents will travel the shortest distances to services, either digitally or locally. This is valuable to hospital administrators as patients with CNMP are more likely to go to the hospitals closest to them. In doing so, knowing the hotspots of CNMP could help illuminate disparities of treatment, and problems with current resource allocation across different individual hospitals within a system.

Historically, digital spatial knowledge has led to improved commerce and the development of smart infrastructure. More recently, epidemiologists have successfully employed spatially linked health data for the purposes of identifying populations of interest, disease management, and the mobilization of humanitarian efforts (Chang et al., 2017; Foresman & Luscombe, 2017; Pearson & Owusu-Edusei, 2017; Stopka et al., 2014; Zhang & Tripathi, 2018). Thus, digital spatial knowledge can improve and guide healthcare initiatives. It is essential, however, that studied entities first be characterized as a "thing" in some manner prior to the application of measurement. While nomenclatures and descriptions for CNMP vary significantly, CNMP as a disorder may best be characterized through its associated demographics, allowing for the application of geospatial principles to CNMP as a disorder.

CNMP Demographics

Data has consistently shown that the prevalence of CNMP varies significantly based on sex, age, race, and socioeconomic status (Dahlhamer et al., 2018; Tauben, Fishman, & Crowley, 2020). As such, each demographic may be its own metric but collectively results in a clearer holistic picture of a CNMP patient, thus lending to demographic layering within the context of geospatial analysis.

Men and women have shown significant differences in reporting not only CNMP but high-impact CP. In the United States, women report experiencing CNMP up to 28% more than their male counterparts (Dahlhamer et al., 2018; Grol-Prokopczyk, 2017; Riskowski, 2014). Women also reported increased rates of high impact CP known to interfere with daily life activities (Dahlhamer et al., 2018; Grol-Prokopczyk, 2017; Tauben et al., 2020). Moreover, women experience a higher level of severity and rate of disability as a result of their CP diagnosis.

Individuals from varying racial groups also experience CNMP at differing rates. Non-Hispanic whites report experiencing CNMP more than any other racial group (Dahlhamer et al., 2018; Grol-Prokopczyk, 2017; Riskowski, 2014; Zelaya, Dahlhamer, Lucas, & Connor, 2020). Minority groups such as Blacks, Native Americans, and Asian Indian populations reported increased incidences of high- impact CP, preventing them from participating in daily activities (Pitcher et al., 2019; Zelaya et al., 2020). Published data, however, may inaccurately represent CNMP prevalence amongst minorities due to inherent socioeconomic disparities, specifically amongst Hispanic and Black individuals (Grol-Prokopczyk, 2017; Portenoy, Ugarte, Fuller, & Haas, 2004; Reyes-Gibby, Aday, Todd, Cleeland, & Anderson, 2007).

Socioeconomic status, however, is more complicated as many subcategories were identified and results were not uniform across all studies. Income level, education status, health insurance, and employment status were the typical determinants of socioeconomic status across multiple studies. Americans in low socioeconomic positions showed higher rates of CNMP (Riskowski, 2014; Yasaei et al., 2021) and were most likely to live below 100% of the federal poverty line (Dahlhamer et al., 2018; Grol-Prokopczyk, 2017; Janevic, Mclaughlin, Heapy, Thacker, & Piette, 2017). In fact, Dahlhamer et al. (2018) identified that populations with household incomes of less than 100% of the federal poverty line were most at risk.

In general, as age increases, the incidence of CNMP also increases, especially starting at age fifty (Dahlhamer et al., 2018; Grol-Prokopczyk, 2017; Zelaya et al., 2020). There exists, however, research that observed stabilization of CNMP rates after the age of 60 (Grol-Prokopczyk, 2017; Janevic et al., 2017; Reyes-Gibby et al., 2007). Chronic nonmalignant pain, however, has been identified as a predictor of death, and Grol-Prokopczyk (2017), connects the loss of follow up due to higher mortality rate in this population as the reason for stabilization, not an actual decrease in CNMP (Dahlhamer et al., 2018; Grol-Prokopczyk, 2017; Reyes-Gibby et al., 2007). This observation, however, is not universal, and strong substantiating evidence exists to support a positive relationship between CNMP and age (Dahlhamer et al., 2018; Grol-Prokopczyk, 2017; Zelaya et al., 2020).

Applicability to Practice

CRNA's are equipped with unique skills to delineate CNMP and other forms of pain, thus providing a more diverse set of approaches to pain management without excessive opioid use. CRNA skill sets align with key points in the Institute of Medicine's (2010) blueprint for CNMP management. First is the necessity to categorize CNMP as a biopsychosocial disorder that considers demographics like age, sex, race, and socioeconomic status. Strategies should focus on populations disproportionately affected by CNMP. This shifts the attention to a population-level strategy for pain management, treatment, and research, which is in line with the shift in the healthcare industry from fee-for-service to value-based reimbursement. In the fee-for-service model, providers are reimbursed for the number of services they supply and not the quality of care. With value-based reimbursement, in the capitation model, providers are paid a set amount per enrollee per month, which incentivizes a long-term commitment to patient health and wellness with a focus on preventative care (Lockner & Walcker, 2018). With these changing reimbursement models, CRNA's will need to shift from a tertiary hospital-based approach to secondary prevention, which requires preemptive treatment in the community. Employing geospatial analysis to identify and make predictions regarding the Orlando CNMP population will help address the gap in the literature. This will directly affect the care CRNA's provide as they are not only responsible for a hospital-based pain management approach but must adapt to a population-based approach through evolving capitation models.

Project Aims

This scholarly project's primary aim is to make predictions of the rate of clustering of CNMP within the specific census tracts within a 30-minute drive time of AdventHealth hospital within Orlando, FL. In doing so, we expected to be able to identify hotspots: higher rates of CNMP clustering. The ultimate goal was to fill an identified gap in the literature regarding rates of CNMP within Central Florida, specifically within Orlando. A secondary aim was to provide AdventHealth Hospital with evidence to inform decision making and appropriate resource allocation for the improvement in the care of CNMP. The project objectives are:

1. Employ descriptive GIS mapping techniques to assess the spatial distribution of CNMP within a 30-minute drive time of AdventHealth hospital within Orlando, FL using census data from 2010.
2. Conduct spatial analysis to determine the location of statistically significant geographic areas of high density and low densities of CNMP within a 30-minute drive time of AdventHealth hospital in Orlando, FL using census data from 2010.
3. Disseminate results of GIS and cluster analysis and the possible implications of significant findings to key players from AdventHealth hospitals within Orlando, FL.

Quality Improvement Framework

The Deming or Plan-Do-Study-Act cycle (PDSA) has been selected to guide this scholarly project (Moen, 2009). The selection of the PDSA cycle results from a recommendation made by a previous study conducted to determine if a need existed for a non-interventional chronic pain service within the AdventHeath University Hope Clinic (Snell et al., 2019). This previous study attempted to determine the prevalence of chronic non-malignant pain within the referring Central Florida AdventHealth system through the analysis of ICD-10 G89 codes. Ultimately, it was determined that the exclusive use of ICD-10 codes resulted in an inexact representation of the CNMP problem. A recommendation was then made to employ the PDSA cycle to further clarify the prevalence of CNMP in future research. A QA/QI framework, therefore, was deemed most appropriate as the goal will be to improve internal processes and practices within AdventHealth (Shirey et al., 2011). The four stages of the PDSA model as they apply to this scholarly project are delineated below.

Plan

This phase required the project planners to understand and delineate the problem, develop objectives, and create a well-planned intervention (Moen, 2009). The "plan" phase or the scholarly project proposal phase has been completed and includes the creation of objectives, a plan delineating what was studied (CNMP hotspots), the population that was studied (high-risk CNMP demographics), and where (Orlando) and when (spring of 2021) it was studied.

Do

The "do" phase began with the submission for review to the Internal Review Board (IRB) in fall 2020. Once the IRB had granted the status of a non-research designation appropriate to this QI/QA project, data analysis began as planned. Any unanticipated problems or important observations were recorded during this phase (Moen, 2009). The "do" phase took place during the spring of 2021.

Study

The "study" phase involved the completion of data analysis, including processing and interpreting the data collected, analyzing what hot spots were revealed, and the census tracts they appeared in, and summarizing what was learned (Moen, 2009). This took place in the fall of 2021.

Act

The "act" phase consisted of a description of project findings and dissemination of these findings to administrators and local key players within the AdventHealth system (Moen, 2009). This has been completed in the spring of 2022.

Methods

This quantitative, retrospective quality-improvement project employed spatial statistical analysis conducted via a geographic information system (GIS), ArcPro 2.6, ESRI, to predict rates of clustering of CNMP populations within a 30-minute drive time of AdventHealth hospital in Orlando, FL. This scholarly project focused on demographically-associated predictors of CNMP that are spatially referenced geographic clusters, or "hot spots."

The study area is in east-central Florida. It covers much of urban/suburban Orlando, FL. This site offers critical analysis of expected CNMP burden that surrounds typical cities in the US. This site encompasses diverse ages, ethnicities and socio-economics. The study area is the 30-minute drive-time service area surrounding a health-care institution in Central Florida (Figure 1A). Thirty-minute drive times are areas of greatest usage by patients for hospitals (Brual et al., 2010). To assess our second goal of uncovering differential CNMP among populations, we subdivided the study area into US Census Bureau Census Tracts (Figure 1B). United States census tracts are defined by visible geographic features and contain an optimum sample size ranging from 1,200 to 8,000 people (United States Census Bureau, 2012).

Hot Spot Statistical Analysis

Hot spot analysis is a statistical method used to identify geographic clustering of spatial phenomena; for our purposes, CNMP populations of interest. The specific spatial statistic method employed was the Getis-Ord Gi statistic (Environmental Systems Research Institute Inc, 2015). This statistical method assesses the frequency of phenomena of interest as a function of spatial separation: a large number of close phenomena are "hotter" than a small number of widely separated cases of the same phenomena. This analysis is performed by the GIS to identify locations of statistically significant high and low values of clustering based on the calculations resulting in z-scores and p-values. Traditionally, analysis is performed on United States census tracts as census tracts are defined by visible geographic features and contain an optimum sample size ranging from 1,200 to 8,000 people (United States Census Bureau, 2012). The GIS contains programmed statistical features that include locational and population attribute data that can then be compared to the entered data set test features, in this case, demographic variables. The demographic variables that figure most prominently in CNMP publications include sex, age, race, and a household income of less than 100% of the federal poverty line (Dahlhamer et al., 2018; Pitcher et al., 2019.) Thus, these demographics, known for their ability to differentiate CNMP affected populations from their counterparts, was compiled into a dataset. This data set was obtained from a previously published national CP census performed by Dahlhamer et al. (2018) and published in 2019. Population attribute data within the GIS is derived from the 2010 United States Census and was used to predict areas within a 30-minute drive time of

AdventHealth hospital, Orlando, FL where CNMP clusters could likely occur. 30-minute drive times prove to be valid models from which to gather a proper time standard (Branas, Mackenzie, & ReVelle, 2000; Brual et al., 2010; Iloglu, et al., 2021; Rocque et al., 2019).

Data analysis on populations within census tracts in Orlando, Florida, was conducted through the built-in functions of the geographical information system (GIS) and addressed the project objectives. Initially, descriptive GIS mapping techniques were conducted to assess the spatial distribution of CNMP in the 30-minute drive time of AdventHealth hospital within Orlando, FL. Specific descriptive statistics employed were counts, percentages, and densities. Once completed, hot spot analysis employing the Getis-Ord Gi statistic was performed to locate statistically significant high- and low-value clusters of CNMP. The resulting statistical analysis produced z-score and p-values. These values are used as predictors of hot spots. A "hot spot" does not necessarily have to coincide with census tract boundaries but produces their own polygon borders, so the term “neighborhood” was used. Since these GIS calculated borders represent non-standardized national, state, or locally defined borders, they are much less available to identify individual CNMP information: only the clinician/researcher would be privy to possibly locating individuals. Nevertheless, we displayed CNMP hot spot/cold spot results in formats that are not amenable to individually identifiable data. Neighborhoods with higher z-scores related to higher degrees of clustering (Environmental Systems Research Institute (ESRI) Inc, 2015). Results of the GIS and cluster analysis and the possible implications of significant findings were disseminated to key players from AdventHealth hospitals in Orlando.

Ethics

This scholarly project was conducted within the AdventHealth University Center for Population Health using publicly available data from prior research and did not include gathering data directly from human subjects. The population attribute data within the GIS is derived from the 2010 United States Census, and comparison demographics was obtained from a 2019 national CP census conducted by the CDC, which resides in the public domain (CDC, 2020). The selected Orlando population was limited to non-institutionalized adults, 18 years or older, resulting in a sample size of approximately 238,300 individuals (U.S. Census Bureau, 2012). During implementation, data underwent secondary analysis, and the demographics selected did not target or seek to identify vulnerable populations. The employment of GIS analysis for this quality improvement project, therefore, superficially appears to meet criteria for exemption from federal regulations related to human subject research as it is secondary data (U.S. Department of Health & Human Services, n.d.). Section 164.514 of the HIPAA Privacy Rule, however, requires that there be no, "reasonable basis" to believe that information be used to "identify an individual" (U.S. Department of Health and Human Services, 2012, p. 6). The HIPAA Privacy Rule further delineates the methods by which federal de-identification standards may be achieved. One of which limits aggregate data to a zip code of no less than 20,000 individuals (U.S. Department of Health and Human Services, 2012). As GIS analysis is performed at the census tract level, which is far more granular than a zip code, there is a theoretical concern with respect to maps and spatial outputs that individual identities might be reengineered with a significant layering of demographics resulting in much finer scales (Ajayakumar, Curtis, & Curtis, 2019; Boulos, Curtis, & AbdelMalik, 2009). However, as our analysis used census-tract level data that was assessed and CNMP relevant and predictive "neighborhoods" that do not correspond to standardized geographic boundaries (see above) were created, we suggest this analysis will result in areas of interest to health practitioners and not be well adapted to individually identifiable analysis. Additionally, the AdventHealth University Center for

Population Health has implemented policies in regard to the physical building security where the GIS is housed, as well as providing the necessary computer and network security. Data storage plans included only accessing the data through the GIS that remains secured and restricted only to authorized researchers in a locked AHU facility.

Those individuals for this scholarly project included Dr. Russ Butler, the director of the Center for Population Research at AdventHealth University, Dr. Sarah Snell, the primary investigator as well as Jessica Bogard and Martin Perry, co-primary investigators. Project data will be retained for seven years after the completion of the scholarly project and kept secure within the GIS software as well as cloud backups. Prior to publication and dissemination, grid masks will be applied/and or other techniques to any images derived from these analyses and was submitted to the director of the Center for Population Research at AdventHeath University for approval to mitigate confidentiality risks. Due to its massive size and complexity, the GIS system is considered big data (Baro, Degoul, Beuscart, & Chazard, 2015). Given the nature and size of the data sets and the minimal risk for reengineering subject identity, a waiver of informed consent was requested as this project could not practically be carried out without the requested waiver.

Planning and Procedures

Please refer to the acknowledgements.

Timeline

After IRB had determined a non-research designation was appropriate to this QI/QA project, data analysis was initiated in January of 2021 utilizing the GIS, pending IRB, and SRC completion at AdventHealth University. Data analysis was conducted by spring 2021. Data analysis implementation and the discussion was finished Fall 2021. Dissemination is to be completed by fall 2021.

Results and Findings

As shown in Table 1, the study area is comprised of 232 U.S. Census Bureau Census Tracts. The Census Tracts (CTs) averaged 4.2 sq km and just over 5200 people. The 30-minute drive time area encompassed just over 982 km^2 and just over 1.2 million people. The total number of people aged 45 years and older, comprised almost exactly 39% of the population. For the three racial categories assessed for CNMP, the percent of the total population >44yrs averaged 12.5% of the population with White's just over 16%, Hispanics 12.5% and Blacks 8.5%.

Just under 132,000 total individuals, >44yrs, were calculated to be CNMP sufferers, or almost 11% of the total population and 28% of people 45yrs and older (Table 1). The calculated White CNMP prevalence was almost twice as high as for either Blacks or Hispanics (Table 1). This result is in part due to Whites comprising a greater proportion of the study-area population and the tendency for Whites to have greater CNMP rates than for the other two racial categories (Table 1). The proportion of women tends to increase relative to men as populations age. For the study-area >44yrs population, women comprised almost 54% and men approximately 46% (Table 1). Our results indicate that almost 14,000 more women could be chronic-pain sufferers than men, or about 36% more women than men (Table 1). The CT spatial-analytics results indicate that distribution of CNMP prevalence is generally not evenly distributed across the study-area (Figure 2).

CNMP prevalence of the total population displays the most spatially regular pattern as compared to all other K-means results; however, the EBK surface results indicate some lower probability areas in the southeastern portion of the study area (Figure 2B). The hotspot analysis reflects the EBK results in that cold spots for CNMP population prevalence occur in the south-central and eastern parts of the study area (Figure 2C). The spatial results of CNMP prevalence for the White population exhibits relatively large areas of low prevalence in the southwest of the study area with clusters in the north and east (Figure 2D, E & F).

In contrast, the results of CNMP prevalence patterns among Black is almost an inverse to that of Whites with Black CNMP highest prevalence and clustering in the study area’s southwest lowest throughout much of the north, east, and southeast (Figure 2G, H & I).

The spatial pattern of highest Hispanic CNMP prevalence formed almost a ring around the study area center (Figure 2J & K). However, Hispanic CNMP hotspots were more pronounced in the study areas southeastern quadrant (Figure 2L). The spatial CNMP prevalence results for the population at 100% FPL and below contains patterns of high prevalence for Black and Hispanic as well as a small area in the northeast that appears to be a combination of White, Black and Hispanic groups (Figure 2).

Discussion, Applicability to Practice, and Contribution to Professional Growth

Discussion

CNMP affects 20% of the world's population, resulting in reduced quality of life, increased debilitating outcomes, and has cost the American healthcare system billions of dollars annually. Though the prevalence of CP is well-established globally and nationally, the literature does not identify prevalence in Florida, much less in the city of Orlando. This scholarly project attempted to fill in these gaps, specifically within a 30-minute drive time radius of AdventHealth Orlando.

GIS and spatial analyses have continued to gain traction in public health in the past decade. The increasing importance of entwining space, geography, social factors, and health with the burgeoning use of technology highlights the role spatial epidemiology must play in assisting in public health measures. In the absence of published CNMP data in Florida, GIS data visualization techniques were used to identify high densities of vulnerable populations who may experience CNMP based on risk factors delineated by the 2016 CDC publication. Areas of high likelihood were noted, particularly in the Apopka tracts, in which many clusters of high disease burden were detected. Conversely, cold spots included communities near Altamonte and Celebration, indicating resources would be less likely to be needed in these regions and would be better utilized in prevalent areas like Apopka. Predicting where patients with CNMP are most likely to live would allow regional hospital systems to allocate resources to specific hospital divisions near identified hotspots. Specifically, the AdventHealth system could divert resources to their Apopka campus to meet and better address this community burden.

The applications of these predictive analyses and the subsequent shifting of resources could have a far-reaching impact by addressing the IOM's six domains of healthcare quality leading to better-directed community outreach care, resource allocation, and efficiency. By directing primary and secondary prevention therapies, hospitals could reduce acute care utilization by better managing patients' CNMP leading to reduced emergency room visits for primary care management and ultimately cost reduction. If successful, this process could extend out towards other diagnoses and reduce the overall community burden.

Recommendations

In future iterations of this PDSA cycle, we will address the six key domains from the IOM. The Institute for Healthcare Improvement's *Across the Chasm: Six Aims for Changing the Health Care System* brings to light six foundational components to address the current health care system's fundamental deficits in remedying these issues. The report asserts that health care systems should be safe, effective, patient-centered, timely, efficient, and equitable across many issues in current health care arising from ongoing health problems that fail to provide viable solutions because they lack addressing these six entities. The author further emphasizes that we cannot reach health goals without multidisciplinary involvement. A multidisciplinary team with specializations in anesthesia, public health, finance, and administration is needed to more effectively guide resource allocation for AdventHealth facilities, focusing on program development and enhancement in hotspot areas like Apopka. It is imperative that providers across disciplines are educated about the area-specific patient population they are serving (prevalent diseases, comorbidities) to treat those with high disease risk factors for CNMP appropriately.

As part of the next PDSA cycle, recommendations include additional research necessary for confirmations of predictive results to assess the predictive value of the geospatial analysis that was used. As discussed above, if the predictive value is high, potential use and capability could be far-reaching. In addition, this project highlights the need for increased attention to CNMP as a condition. This study area included 132,000 individuals predicted to have CNMP.

Social factors identified from the 2016 CDC publication included poverty level, age, sex, and race. The social factors within the 30 minute drive time which yielded the most notable hot spots most likely to experience CNMP were found to be at or below 100% of the federal poverty line and age greater than 44 years. Further, neighborhoods with increased age and poverty have shown the greatest predictive risk and concentration of CNMP. Those at the highest risk of CNMP are the most economically vulnerable.

Chronic pain is often mistreated with opioid narcotics even though opioid analgesics are shown not to be an effective treatment for CNMP (Meuser et al., 2001; Yasaei et al., 2021). Effective non-pharmacological treatments include cognitive-behavioral therapy (CBT), manipulation, acupuncture, biofeedback, massage, and pain rehabilitation programs (Bonakdar et al., 2019). However, historically, these treatments are not covered by Medicare & Medicaid, which may contribute to why these treatments continue to be underused. Thus, increased funding is needed to improve patient access. In addition, political advocacy may be required to facilitate this process. Concurrently, increased education regarding the risks and poor efficacy of opioids for the treatment of CNMP focused on providers with prescriptive authority would immediately improve outcomes and decrease opioid dependency for this population (Dorr & Townley, 2016). Until health care coverage for non-pharmacological treatment improves, current hospital spending should be reallocated from opioid-based treatments to multi-modal analgesics and non-pharmacologic treatments. It is important to understand treating chronic pain is based on a continuum and pain treatment should be individualized to the patient.

Applicability To Healthcare

CRNAs are uniquely qualified to lead population health initiatives with a focus on chronic pain because of the incorporation of population health within the essentials of undergraduate nursing curriculum and their extensive education in acute and chronic pain management (AACN, 2008; IOM, 2011). CRNAs also have a responsibility to society to address problem areas in public health and that responsibility requires collaboration with other professions (AANA, 2018). However, healthcare professions have a tendency to operate in silos and this isolation can hinder progress and result in short-sighted views that offer incomplete solutions. Integration with other professions and stepping out of these silos can bring about the ability to contextualize problems into grander intellectual landscapes that provide new revelations from current research (Hofmeyer et al., 2007). Thus expertise from other disciplines is required to ultimately solve complex population health issues.

Limitations

Limitations identified include a lack of control variables such as variations in terminology generalizing CP without delineating non-malignant chronic pain or non-cancer chronic pain. This lack of specificity impacts the reliability of the CDC's seminal study that includes a large sample size of national data. Moreover, an acknowledgment that there may be a gap in the delineation of non-cancer pain from CP statistics when applied to the GIS needs to be considered. By nature of the study, CNMP population data was indirect and did not contain actual point sampling of the population, rather it predicted risk propensity based on national data and projected that locally. Actual CNMP hotpots might vary and point data collection would be the next step in this research.

Conclusion

CNMP unequivocally causes multilayer issues, including poor quality of life, exhausted resources, and millions in national debt every year. Thus, locating high-risk populations for CNMP is imperative to address these issues and allocate the necessary resources. Multiple geospatial analyses can be effectively used to identify these high-risk populations to accomplish this goal. Further, there is a clear role for CRNAs in population health settings. Hopefully, this scholarly project will increase awareness of CNMP amongst hospital leadership and healthcare providers in the Orlando region.

Dissemination Plan

This scholarly project will be locally disseminated based upon identified hotspots, geographically near AdventHealth hospitals. Specifically, results will be presented to interested key players, as well as to receptive administrators within AdventHealth hospitals. Dissemination will also possibly include anesthesia conferences, such as FANA and AANA, as well as submission for publication in a peer reviewed journal amenable to quality improvement topics.

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Figures and Tables

Table 1: *Demographic Data for Adult Population in Study Area in Orlando Florida*

Total Population	
Total Area	982.5 sq km
Number Census Tracts	232
Total Population (2020)	1,207,613
Total Population >44yrs	467,844
Calculated Total CNMP >44yrs	131,932
Population by Race/Ethnicity	
Hispanic Population	375,089
Hispanic Population >44yrs	151,141
Calculated Hispanic CNMP >44yrs	22,981
Black Population	256,026
Black Population >44yrs	103,165
Calculated Black CNMP >44yrs	16,333
White Population	491,236
White Population >44yrs	197,942
Calculated White CNMP >44yrs	43,250
Population by Gender	
Total Male Population >44yrs	216,532
Calculated Male CNMP >44yrs	38,543
Total Female Population >44yrs	251,308
Calculated Female CNMP >44yrs	52,505
Total Population at 100% FPL or less	48,232
Calculated CNMP 100% FPL or less	13,409

Figure 1A-B

Figure 1

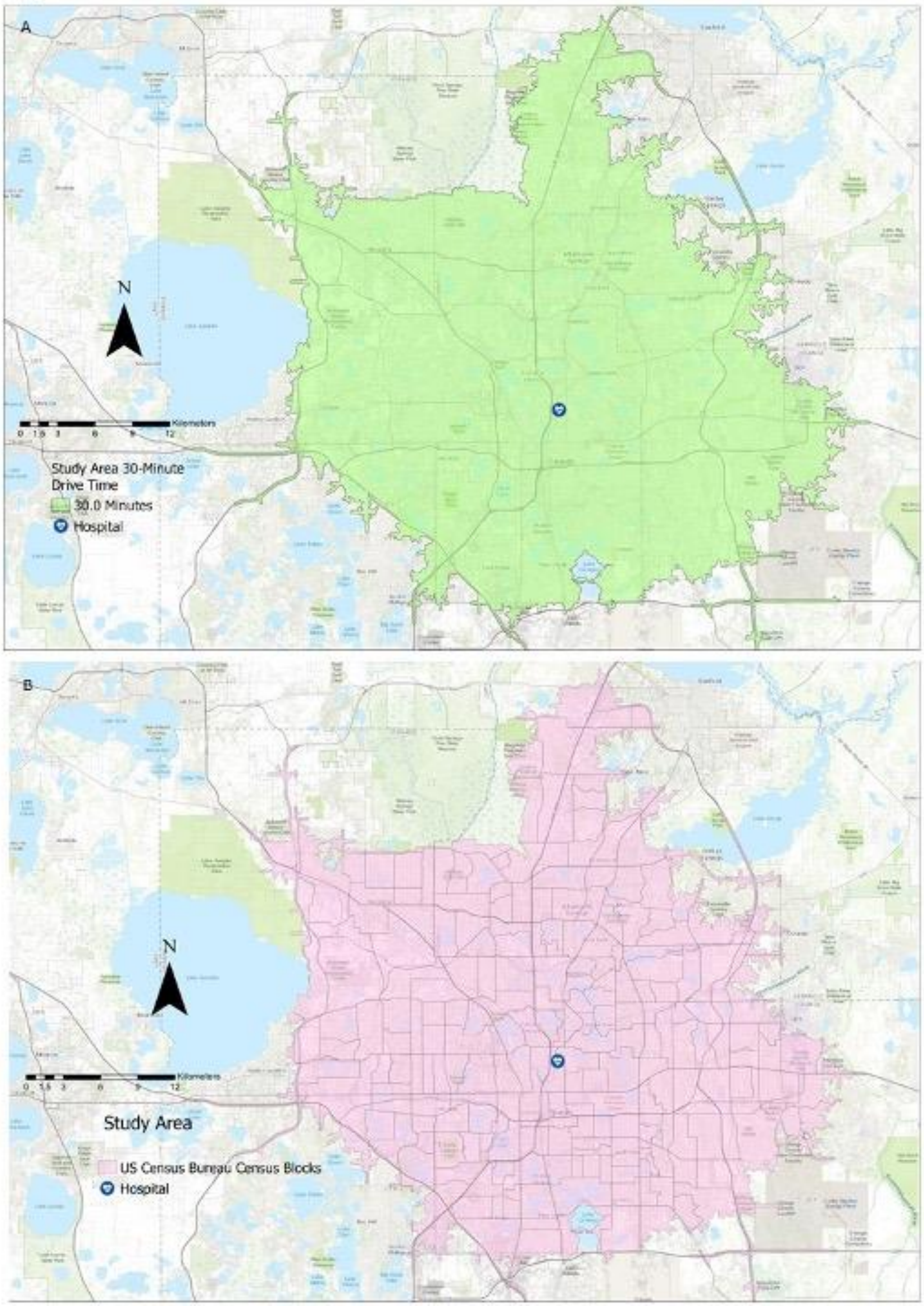

Figure 2A-V

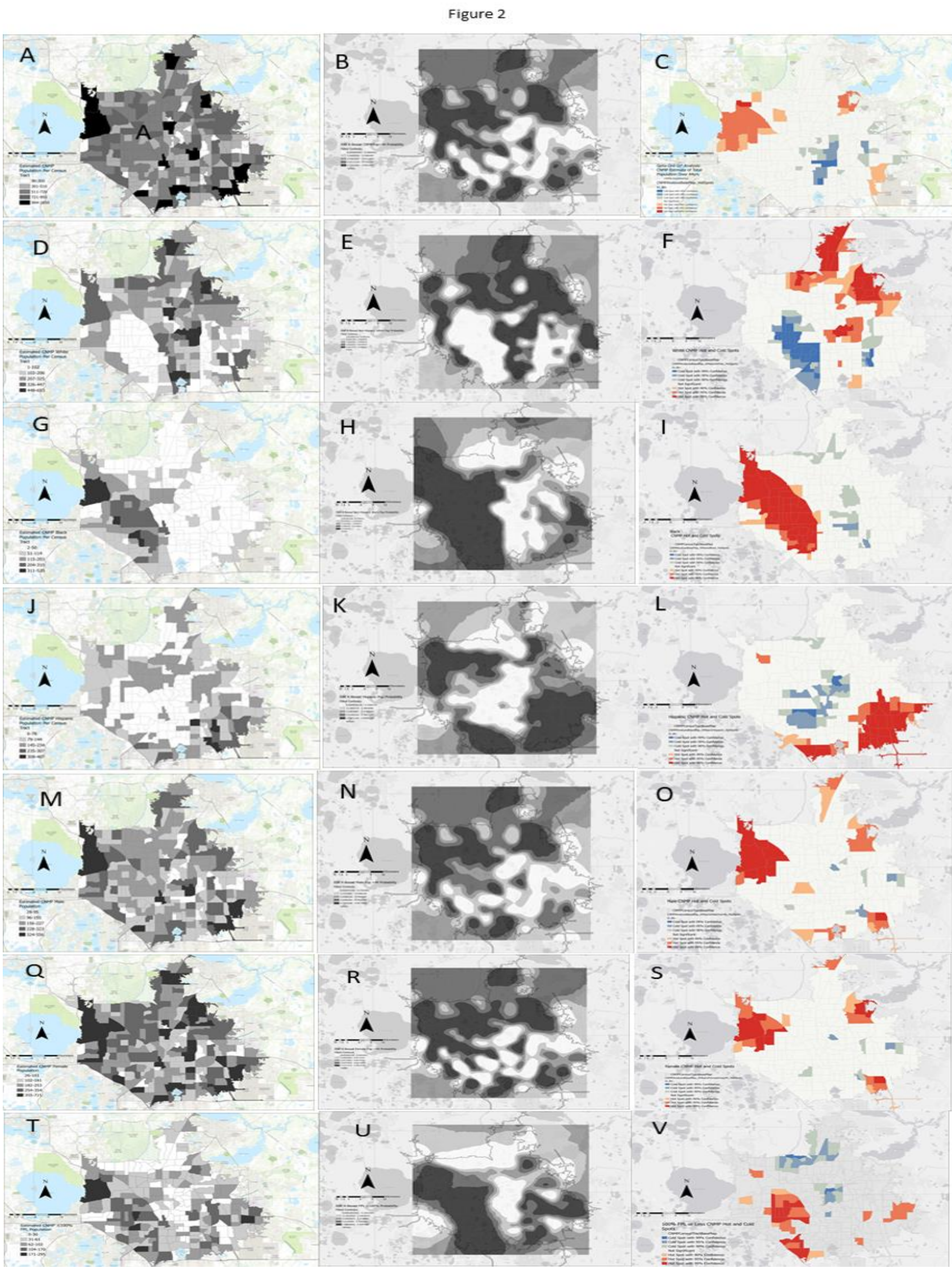

Figure 3

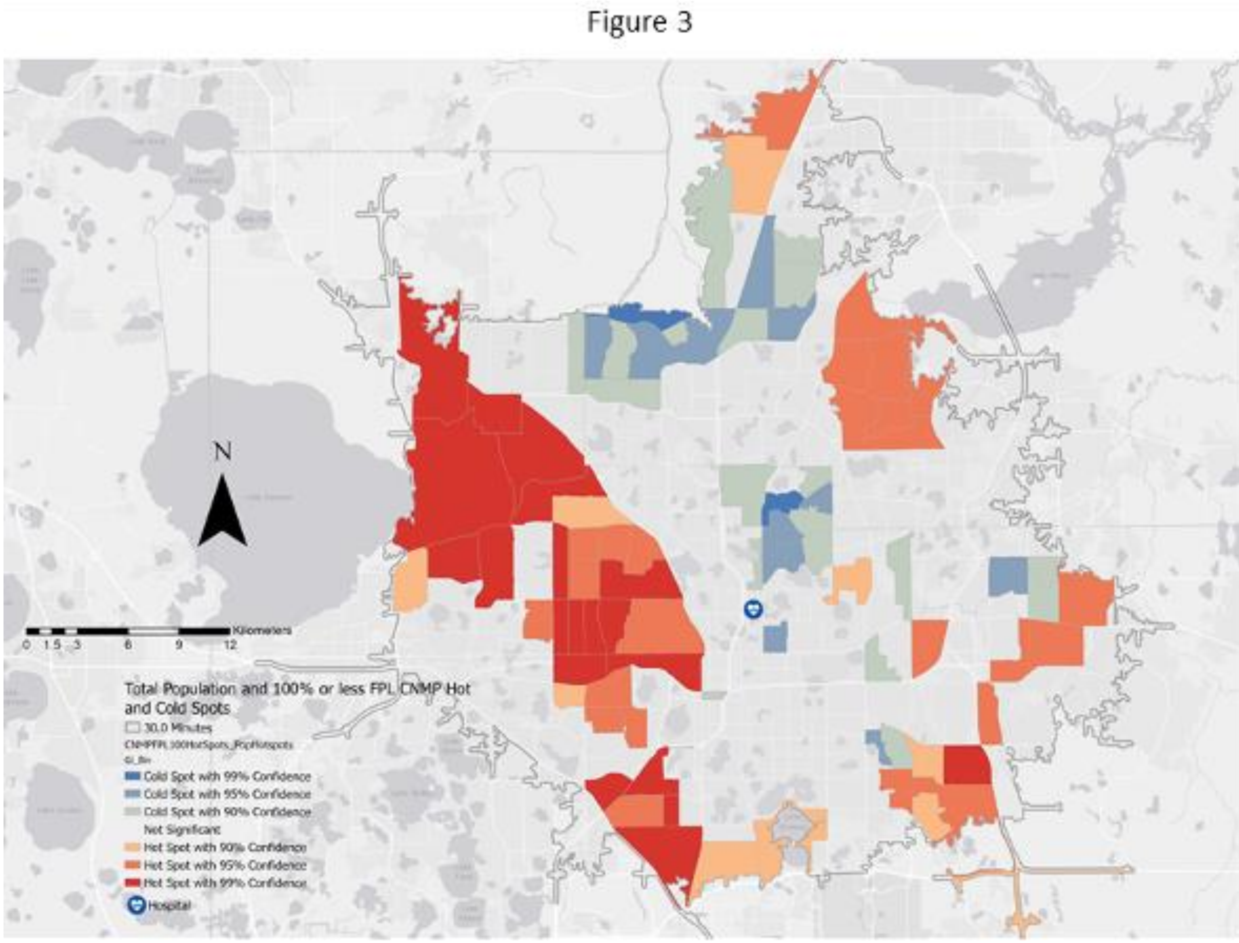
Figure 3
N
0 1.5 3 6 9 12 Kilometers
Total Population and 100% or less FPL CNMP Hot and Cold Spots
30.0 Minutes
Cold Spot with 99% Confidence
Cold Spot with 95% Confidence
Cold Spot with 90% Confidence
Not Significant
Hot Spot with 90% Confidence
Hot Spot with 95% Confidence
Hot Spot with 99% Confidence
Hospital

MATRIX TABLE

<table>
<tr><td colspan="6">Bibliography

Foley, R., & Ibrahim, H., Shmagel, A., (2016). Epidemiology of chronic low back pain in US adults: Data from the 2009–2010 national health and nutrition examination survey. Arthritis Care & Research, 68(11), 1688-1694. doi:10.1002/acr.22890
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<tr><td>Purpose</td><td>Variables</td><td>Setting/Subjects</td><td>Measurement and Instruments</td><td>Results</td><td>Evidence Quality</td></tr>
<tr>
<td>Study One
Describe the population characteristics and relationships with increased health care use in US adults with chronic low back pain (LBP).

Study Two
To compare chronic pain in Miami-Dade County, FL versus the U.S. population</td>
<td rowspan="3">Study One
Primary outcome: incidence of chronic LBP.

Secondary outcome: Demographic characteristics compared between those with LBP and those without.

Study Two
Primary Outcome: Chronic pain prevalence

Secondary Outcome: Chronic back, migraines, and neck pain</td>
<td rowspan="3">Study One
Setting: Throughout the US
Subjects: 5,103

Study Two:
Setting: Not specified

Subjects: 2,700 18 years and older</td>
<td rowspan="3">Study One
National Health and Nutrition Examination Survey (NHANES)

Study Two
Professional Research Consultants Community Health Survey</td>
<td>Study One
The rate of chronic LBP in US adults ages 20–69 years was 13.1%. The incidence of chronic LBP increased with age, with the highest rate in the 5th and 6th decades of life 95% CI 2.03 (1.48-2.78) and 2.07 (1.59-2.71).

Study Two
-21% chronic back pain in Miami-Dade, FL compared to 21.5% to in the U.S.
-11.3% chronic neck pain in Miami-Dade, FL compared to 8.3% in the U.S.
-15.6% chronic migraines in Miami-Dade, FL compared to 16.9% in the U.S.
- 80% of Americans have LBP. Second leading cause of lost work time, third most common reason to have surgery, fifth most frequent cause of hospitalization.</td>
<td rowspan="3">Study One
Methodological flaws: Mostly self-report assessment, vulnerable to recall bias and inaccuracies.
Inconsistency: None.
Indirectness: Cannot account for multiple possible sources of chronic LBP
Imprecision None.
Publication bias None

Study Two
Methodological flaws: Non-English and non-Spanish speakers, the homeless, and incarcerated were excluded.
Inconsistency: Based on 12 neighborhood clusters and 1 oversampled cluster
Indirectness: None in this study.
Imprecision: None in this study.
Publication bias: None in this study.</td>
</tr>
<tr><td>Design</td><td>Implications</td></tr>
<tr>
<td>Study One
Survey

Study Two
Randomized Survey</td>
<td>Study One
This study found that there is a statistically significant incidence of LBP in the United States. LBP populations in the US during 2009–2010 were less educated, less wealthy, more likely to smoke, have depression, sleep issues, and other medical diseases than those without chronic LBP.

Study Two
Rates of chronic pain are identical (if not higher) in Miami-Dade county versus the U.S. nation.</td>
</tr>
</table>

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Bibliography

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Dahlhamer, J., Lucas, J., Zelaya, C., Nahin, R., Mackey, S., DeBar, L., . . . Helmick, C. (2018). Prevalence of chronic pain and high-impact chronic pain among adults-United States, 2016. *MMWR. Morbidity and Mortality Weekly Report, 67*(36), 1001-1006. doi:10.15585/mmwr.mm6736a2

Purpose	**Variables**	**Setting/Subjects**	**Measurement and Instruments**	**Results**	**Evidence Quality**
Study One To determine the sociodemographic population of debilitating CP and CP without limits. **Study Two** To identify the widespread presence and demographics of chronic pain versus high-impact CP in the U.S.	**Study One** Primary outcome: CP **Secondary outcome**: Age, sex, marital status, race, education level, BMI, regional location, comorbidities, pain intensity, activity limitations, mental health influence **Study Two** Primary outcome: CP **Secondary outcome**: Age, employment status, poverty status, race, health care coverage type, sex, education level, urbanicity, veteran, non-veterans	**Study One** Setting: Surveys sent to noninstitutionalized households Subjects: 15,670 randomly selected individuals for sample survey experiencing chronic pain from 3 to 6 months or more **Study Two** Setting: Surveys sent to noninstitutionalized households Subjects: 33,028 people ≥ 18 years of age with chronic or high-impact chronic pain for 6 months or more	**Study One** 2011 National Health Interview Survey via National Center for Health Statistics (NCHS) **Study Two** 2016 National Health Interview Survey via National Center for Health Statistics (NCHS)	**Study One** 10.6 million (4.8%) Americans reported high impact chronic pain restricting one or more major life activity in 2011. Disability was associated with chronic pain than any other comorbidity (95%CI 3.73-5.26). Women were more likely to report chronic pain (95%CI OR=1.16, 1.03-1.30). Ages >45 more prevalent. 18.4% >40 million experience pain lasting more than 3 months. **Study Two** 50 million (20.4%) reported chronic pain. 19.6 million (8.0%) claimed they had high-impact CP (95%CI 19.7-21.0, $p<0.05$). Unemployed, non-Hispanic white females with less than a Bachelor's degree are the most prevalent for both subsets of chronic pain.	**Study One** Methodological flaws: Population selection bias, nonresponse bias. Veterans, active duty military, incarcerated inmates, residential care facilities are not included in the survey. Inconsistency: None in this study. Indirectness: The article did not specify the type of research design they implemented, but was inferential. Imprecision: None in this study. Publication bias: None in this study.
Design **Study One** Cross-sectional survey **Study Two** Cross-sectional survey				Implications **Study One** Differentiating high-impact chronic pain from CP without limitations is significant in future pain relief modalities and preventing chronic pain without limitations to transition to a debilitating state. **Study Two** Providing more accurate demographical statistics about chronic and high-impact pain in an effort to bring attention to alternative pain intervention, educate the population about realistic expectations about pain relief, and inform federal policymakers about the pain crisis and to provide better resources.	**Study Two** Methodological flaws: Recall bias, no blinding, population exclusions (active military, long-term health care facilities, prison inmates). Inconsistency: None in this study. Indirectness: None in this study. Imprecision: None in this study. Publication bias: Grants received from Pfizer Inc.

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<table>
<tr><td colspan="6">Bibliography

Grol-Prokopczyk, H. (2017). Sociodemographic disparities in chronic pain, based on 12-year longitudinal data. Pain, 158(2), 313-322 doi:10.1097/j.pain.0000000000000762
Riskowski, J. L. (2014). Associations of socioeconomic position and pain prevalence in the united states: Findings from the national health and nutrition examination survey. Pain Medicine, 15(9), 1508-1521. doi:10.1111/pme.12528</td></tr>
<tr><th>Purpose</th><th>Variables</th><th>Setting/Subjects</th><th>Measurement and Instruments</th><th>Results</th><th>Evidence Quality</th></tr>
<tr>
<td>Study One
12-year study analysis of a biannual survey to decrease measurement bias that is seen in many CP surveys that are cross-sectional and display socioeconomic disparities

Study Two
To identify the relationship between socioeconomic status, race, and ethnicity with CP in the U.S.</td>
<td rowspan="3">Study One
Primary outcome: Chronic pain disparities

Secondary Outcomes:
Age categories, sex, education, race, survival status, household income

Study Two
Primary Outcome: Chronic pain

Secondary Outcomes:
Socioeconomic status, sex, age in relation to widespread or regional chronic pain</td>
<td rowspan="3">Study One
Setting:
National Institute of Aging at the University of Michigan

Subjects:
19,776 people above the age of 50 experiencing chronic pain

Study Two
Setting:
Institute for Allied Health Research at Caledonian University, Glasgow, United Kingdom

Subjects:
8,270 participants at least 18 years of age that has chronic pain</td>
<td rowspan="3">Study One
Analysis of seven biennial data nationally from the Health and Retirement Study from 1998-2010

Study Two
2003-2004 National Health and Nutrition Examination Survey (NHANES) via the U.S. National Center for Health Statistics</td>
<td>Study One
Pain persisted and increased after the age of 60 when varying reports say pain plateaus after 60 years old. Pain is largely attributed to economic status and disability. Many with poor socioeconomic status are have an increased likelihood to be perceived as “exaggerative” by health professionals.

Study Two
Chronic pain prevalence is 14.5% (13.4-17.7%). Women having a higher prevalence rate than men 18.3% (95% CI 15.1-21.5%). Women 40-64 years and 65–84 years of age reported greater rates of chronic widespread pain than males.
CP prevalence was 15.6% (13.4-17.7%), with non-Hispanic white people having a higher prevalence than those in other racial and ethnic groups.</td>
<td rowspan="3">Study One
Methodological flaws: Heterogeneity, non-response bias, restricted to 50 years old population, unclear definition of “pain” or “persistent pain” in survey.
Inconsistency: None
Indirectness: None
Imprecision: None
Publication bias: None

Study Two
Methodological flaws:
Excluded data from the homeless, those institutionalized, without a telephone landline, those who were not 18 years old,
or did not complete the pain questionnaire.
Inconsistency: None in this study.
Indirectness: None in this study.
Imprecision: None in this study.
Publication bias:
Article did not specify if they did or did not have any biases</td>
</tr>
<tr><td>Design</td><td>Implications</td></tr>
<tr>
<td>Study One
Secondary study of a cross-sectional survey

Study Two
Cross-sectional survey analysis</td>
<td>Study One
Disparities within the way pain is measured is inconsistent with several pain surveys. Category limitations must be broad (i.e. age) and clearly defined definitions and descriptions of pain.

Study Two:
Socioeconomic status has a correlation to the severity, type, and location of pain. People in the lowest socioeconomic class had increased reports of chronic pain between 40-64 years old. CP in ≥ 85 years there is a decrease in pain in the lower socioeconomic class. Higher reports of back and upper/lower extremities in the lower socioeconomic population.</td>
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Bibliography

Portenoy, R. K., Ugarte, C., Fuller, I., & Haas, G. (2004). Population-based survey of pain in the United States: Differences among white, african american, and hispanic subjects. *The Journal of Pain, 5*(6), 317-328. doi:10.1016/j.jpain.2004.05.005

Janevic, M. R., Mclaughlin, S. J., Heapy, A. A., Thacker, C., & Piette, J. D. (2017). Racial and socioeconomic disparities in disabling chronic pain: Findings from the health and retirement study. *The Journal of Pain, 18*(12), 1459-1467. doi:10.1016/j.jpain.2017.07.005

Purpose	**Variables**	**Setting/Subjects**	**Measurement and Instruments**	**Results**	**Evidence Quality**
Study One To assess a large, racially diverse, population >51 years old for correlation between race and socioeconomic factors and the impact of CP and disabling pain. **Study Two** To assess the prevalence of high-impact CP in U.S. adults over age 50 overall and within population subgroups.	**Study One** Primary outcome: Racial and ethnic variations in pain experience and treatment preferences. **Secondary outcome**: Race (White, African American, Hispanic) Sex, age, employment status, education level, annual income **Study Two** Primary outcome: Pain duration, intensity and impact. **Secondary outcome**: *Age*, *sex*, *race* (non-Hispanic black, non-Hispanic white, Hispanic, other), *education* (less than high school, high school diploma or equivalent, more than high school) and quartiles of *total household wealth*	**Study One** Setting: The American Pain Society Subjects: 454 Caucasians, 447 African Americans, and 434 Hispanics; 1592 qualified for the study. **Study Two** Setting: Biennial phone and in-person surveys of a nationally-representative sample of community-dwelling Americans over age 50 Subjects: Data are from a subsample of HRS respondents (n=1,925) who were randomly selected for a supplementary pain module in 2010 all over age 50.	**Study One** Screening question interview via telephone survey developed by Russel Research. **Study Two** From over 20,000 HRS people surveyed in 2010, HRS investigators chose a random set of 1,925 self-respondents who were screened after for any signs of pain using an item asking whether during the past year they had experienced pain that lasted one week or longer. Use of bivariate logistic regression models to identify the relationship between each demographic and health variable and the presence of high-impact chronic pain.	**Study One** - Whites had pain substantially longer than African Americans (9.9 [10.8] years compared to 7.6 [10.0] years; P<.001) or Hispanic subjects (9.9 [10.8] years compared to 6.5 [8.6] years; P < .001. - Disabling pain (35.8%) did not different across racial-ethnic groups; (female, < $25,500 income, lower than a high school degree, and divorced) significantly associated with it. **Study Two** Overall, 8.2% (95% C.I.=6.7 to 10.1%) of adults over age 50 qualified for high-impact chronic pain. This subset increased to 17.1% (95% C.I.=12.3 to 23.4%) among people in the lowest wealth quarter.	**Study One** Methodological flaws: The questionnaire in the survey reportedly was not validated. Inconsistency: Recall bias, nonresponse bias, or the desire to appear socially desirable could have altered the results. Indirectness: none Imprecision: none Publication bias: none reported **Study Two** Methodological flaws: Recall bias, Heterogeneity, non-response bias, restricted to > 50 years old population Inconsistency: Chronic pain subgroup including those with 2-3 months versus >3 months, not consistent definition. Indirectness: None in this study. Imprecision: None in this study. Publication bias: None in this study.
Design				Implications	
Study One Cross-sectional telephone survey analysis **Study Two** Secondary analysis of cross-sectional survey				**Study One** - Socioeconomic disadvantages are more of an important predictor of disabling pain than race/ethnicity. **Study Two** Prevalence differences by race, education, ethnicity and age were not significant. Arthritis and depression were greatly associated with high-impact pain in multivariable analysis. Among adults with *any* chronic pain, African Americans and individuals in the lowest wealth quarter claimed increased pain-related disability.	