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Geographic Modifiable Risk Factors for Alzheimer's Disease and Related Dementias Amid Chronic Disease in the United States

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Walden University
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Abstract

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MS, University of Maryland University College, 2015

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Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Philosophy

Public Health

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Abstract

Alzheimer's disease and related dementias (ADRD) prevalence increase in the United States throughout the past 4 decades, coupled with the adverse effects of social determinants of health inequalities (SDoH), represents a public health problem. These issues merit attention primarily due to the neurodegenerative nature of ADRD, which disproportionately imposes health and financial burdens on the patient, family, caregivers, and society, especially in chronic disease, lower-income demographics, and related economic minorities. ADRD prevalence intertwines with SDoH in a spatiotemporal varying relationship, which, if unattended, could become the genesis of a disease-poverty conundrum affecting current and future generations of Americans. The purpose of the study was to evaluate the association between ADRD prevalence and SDoH (educational attainment, income, housing, and pollution) in the context of T2DM and hypertension. This quantitative cross-sectional design was rooted in the SDoH framework. Data from combined secondary datasets from the U.S. 2018 County Health Rankings & Roadmaps and the Centers for Medicare & Medicaid's multiple chronic diseases were analyzed using multiple linear, geographically weighted, and multiscale geographically weighted regression to identify statistically significant relationships between ADRD prevalence and SDoH, T2DM, and AH. Results showed that ADRD was associated with T2DM, AH, and SDoH variables. Positive social change implications include helping policymakers, researchers, and practitioners devise and implement culturally sensitive public health strategies that empower communities in a sustainable positive social change approach that mimics a circular economy system.

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Dedication

This study is dedicated to the memory of my mother, Graciela (Mamacho), who always taught me to seek truth in life, and to my father, Rufino (Chocolate), who always showed me the value of hard and honest work in life. I will always be thankful for their efforts and struggles to raise their children. This study is also dedicated to my beautiful family, Sofi, Rafito, and my wife Ani, whose support and care enabled me to complete this work. It is also dedicated to all the beautiful women who shape my life and represent society's fundamental pillars. My lifelong gratitude extends to them and all the teachers whose lives also blessed my path.

Acknowledgments

Words cannot express my gratitude and thankfulness to God and those who inspired and guided me through this endeavor. To my mentors, Dr. Banerjee and Dr. Dunn, I express my gratitude for their devoted help, support, and patience in making this dissertation possible. They knew what this achievement meant to me and my family. Moreover, they knew of my spiritual drive to make this humble academic contribution. I also acknowledge my family—my wife, Ani, and my children, Rafael and Sofia—whose unconditional love, understanding, and support held me up in the most challenging moments of this journey. To my parents, Mamacho and Chocolate, who taught me that kindness and perseverance will achieve our dreams through hard work. To my sister, Rosa, and my brothers, Danny, Sergio, Ricky, and Jorge, with whom I learned the meaning of family and the value of its unity, may our children learn that from us. To all of you, I want to promise while praying to God that this dissertation shall be (a) the cornerstone of a reengineered life possible through your support and that of the U.S. Veterans Administration and (b) the beginning of giving back to my sisters and brothers who served and are serving our country.

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Chapter 1: Introduction to the Study

Alzheimer's disease and related dementias (ADRD) affect people regardless of age, ethnicity, or socioeconomic status, yet they disproportionately affect human health, development, and economic growth in lower-income demographics and related economic minorities. Disparities and inequalities in the burdens of ADRD are related to social determinants of health inequalities (SDoH). Hence, the cumulative negative impacts of SDoH, which govern human health dynamics, development, and economic growth, shall be understood as contextually modifiable risk factors for disease outcomes (Bhunia & Shit, 2019; Center for Disease Control and Prevention [CDC], 2022).

The prevalence of ADRD has had a sustained increased in the United States and globally over the past 4 decades. This increase in prevalence, coupled with the adverse effects of contextual SDoH, represents a public health problem for society. Addressing these issues is needed primarily due to the neurodegenerative nature of ADRD, which disproportionately imposes health and financial burdens on the patient, family, caregivers, and society, especially in chronic disease, lower income demographics, and related economic minorities (CDC, 2022; Kumar et al., 2018). ADRD prevalence intertwines with SDoH in a spatiotemporal varying yet modifiable relationship, which, if unattended, could become the genesis of a disease-poverty conundrum affecting current and future generations of Americans. In this study, I evaluated the association between ADRD prevalence and SDoH (namely educational attainment, income, housing, and pollution) in the U.S. context of chronic diseases, namely type 2 diabetes mellitus (T2DM) and arterial hypertension (AH), two of the ADRD-related comorbidities and

leading causes of death in the United States. Elucidating the associations between ADRD and SDoH as influences on chronic disease could clarify avenues of research not just on the underlying pathophysiological mechanisms of ADRD and comorbidities (i.e., low-chronic inflammation) but on the adverse effects of SDoH on these associations.

Moreover, understanding the associations among disease outcomes and explanatory variables may help public health practitioners and researchers to devise better contextual and culturally sensitive public health strategies that incorporate the community in the decision-making process. Hence, this study could enhance awareness and catalyze sustainable positive social change that mimics a circular economy system from within the community. A key premise of the study is the need to empower women, who, besides having disproportionate disease rates, also provide critical financial and support for their family, supporting young and older generations, often sacrificing or delaying their own personal and professional growth across socioeconomic and cultural spectrums.

This chapter includes 12 sections. The Background section focuses on ADRD's increased prevalence in the U.S. context of SDoH, T2DM, and AH. It also includes an overview of the identified literature gaps concerning ADRD prevalence and SDoH in the context of T2DM and AH. In the Problem Statement and Purpose of the Study sections, I identify the sustained increase in ADRD prevalence as the public health problem that elicited this study, and I discuss the need to statistically evaluate the association between ADRD prevalence and geographically varying SDoH (namely educational attainment,

income, housing, and pollution) in the U.S. context of T2DM and AH. The next section includes the research questions (RQs) and hypotheses for the study.

In the Theoretical Framework section that follows, I provide an overview of the SDoH framework, focusing on how imposed SDoH affect human health dynamics and related outcomes. I examined the five domains of the SDoH framework through the lens of the social-ecological model (SEM; Bronfenbrenner, 1975), the polarities of democracy (PoD) model (Benet, 2013), and the health belief model (HBM; Strecher & Rosenstock, 1997). The Nature of the Study section includes information on the variables and methods for this study, and the Definitions section sheds light on the nomenclature used throughout this study and the field. In the next three sections—Assumptions, Scope and Delimitations, and Limitations—I respectively address the assumptions undergirding the study, the boundaries of the study, and factors that could lead to a methodological weakness or biases related to this study. The Significance section includes discussion of the study's potential implications for research and practice in the public health field and for positive social change. Last, in the Summary section, I highlight the most significant aspects of this chapter.

Background

I focused on ADRD's increased prevalence in the U.S. context of SDoH, T2DM, and AH. There is an identified literature gaps concerning ADRD prevalence and SDoH in the context of T2DM and AH. Dementia is not a specific disease; it entails a conglomerate of, thus far uncurable, neurodegenerative diseases that progressively concatenate in cognitive and motor control impairment and, subsequently, dementia,

often signaled by memory loss. The five domains of the SDoH framework encompass the SEM, HBM, and PoD model. Dementias affect people by impairing their proper function at the personal, interpersonal, familial, community, and societal levels as evaluated from the SEM perspective. Although dementia is most often observed in adults over 65 years of age, it is not a part of a normal aging process. Instead, it entails a combination of effects between genetic load and the cumulative adverse influence of contextually found SDoH (Kumar et al., 2014). Among ADRD are Alzheimer's disease (AD); vascular dementia (VD); Lewy body dementia; and frontotemporal, mixed, and reversible dementias (Centers for Disease Control and Prevention [CDC], 2019; Kumar et al., 2014; National Institutes of Health [NIH], 2023).

AD accounts for 60% to 70% of dementia cases in the United States, and the CDC (2018) projected a three-fold increase in the incidence of AD over the next 4 decades (see also Mielke, 2018). Data from the National Centers for Health Statistics of the CDC indicated that AD was the sixth leading cause of death (31/100,000) in the United States in 2021 (Xu et al., 2022). Death-related dementia has increased by more than 146% in the last 2 decades. In 2021, more than 6 million adults over the age of 65 were diagnosed with AD. Many other yet undiagnosed cases would point to a greater prevalence (Wong, 2020). ADRD impose health and financial burdens on society. In 2020, the U.S. AD-related care cost was $305 billion; approximately 67% was paid by Medicare and Medicaid (Alzheimer's Association [AA], 2020). Medicare dementia-related care expenditure was 3 times the cost of care for all other conditions. Medicaid spent, on average, 23 times more on dementia-related care costs than for other conditions. Patients’

direct cost was 22% (AA, 2020). Wong (2020) projected the U.S. dementia care expenditure to rise to over $1 trillion, a cost that would be compounded by the increasing life expectancy of the U.S. population (Congressional Budget Office, 2022; MacArthur Foundation, 2014).

In the United States, based on gender only, women bear a two-fold higher risk for ADRD than men. These risks are often related to physiological and psychological changes that women experience throughout their lives, especially around the age of menopause. The changes involve similar pathophysiologic mechanisms (i.e., low-chronic inflammation) also present in T2DM, AH, cardiovascular disease (CVD), osteoporosis (OP), rheumatoid arthritis (RA), and physiological changes in menopause (Groeneveld et al., 2018; Mielke, 2018; Pahwa et al., 2021; Rosselli et al., 2022; Schikowski & Altuğ, 2020).

Furthermore, although ADRD affect people from all walks of life regardless of age, ethnicity, or socioeconomic status, they disproportionately affect lower income demographics and related economic minorities. The disparities and inequalities of the burdens of ADRD, affecting human health dynamics and related outcomes, human development, and related economic growth, correlate to the cumulative spatiotemporal and contextually varying exposure to the modifiable adverse effects imposed by related SDoH. In 2015, the average dementia yearly cost per patient in the United States was approximately $47,617.5, 32% more than the average in Europe; it represented approximately 85% of the U.S. median household income (MHI) and over 196% of U.S.

poverty threshold for a family of four for the same year (Cantarero-Prieto et al., 2020; U.S. Census Bureau, 2016; U.S. Department of Health and Human Services, 2023).

The SDoH entail all nonmedical factors affecting health dynamics and related outcomes, thus including the sociopolitical settings in which people are born, grow, work, live, and age, alongside the natural and built environment and the socioeconomics and social_political constructs that shape and condition daily life (CDC, 2022). Hence, it is crucial to recognize, evaluate, and address the adverse effects of contextual SDoH as modifiable risk factors to human health dynamics and related outcomes, human development, and related economic growth. The Alzheimer's Association (2020), Mishra et al. (2020), Majoka and Shimming (2021), and Röhr (2021) agreed that these inequities and inequalities can also be evaluated from the perspective of race/ethnicity as it often relates to the socioeconomic stratification and related disease burden imposed by SDoH. To these effects, data from the Alzheimer's Association (2020) pointed out these disparities showing differences between risk ratio and diagnosis of dementia by race and ethnicity. Th AA (2020) indicated that, on average, non-Hispanic African Americans are twice as likely than non-Hispanic Whites to have AD. However, only 34% of non-Hispanic African Americans are more likely to have a diagnosis. Similarly, Hispanics are one and a half times as likely as non-Hispanic Whites to have AD. However, only 18% of Hispanics are more likely to be diagnosed. Moreover, Medicare dementia per-patient related cost in 2014 among these ethnic groups was similar for all three groups: $21,174 for non-Hispanic Whites, $28,633 for non-Hispanic African Americans, and $22,694 for Hispanics (AA, 2020). Furthermore, T2DM and AH are recognized as the most common,

genetically related risk factors for ADRD (Alzheimer's Association, 2020; Mishra et al., 2020; Majoka and Shimming, 2021; Röhr, 2021).

Although researchers have investigated several factors affecting ADRD, the existing literature needs more focus on five major factors believed to influence the prevalence, development, and onset of ADRD. These include (a) the influence of SDoH on the prevalence of ADRD in the population and its development and onset at the individual levels, (b) the spatiotemporal relationship effects of exposures (SDoH and related environmental pollution), and ADRD in the U.S. context of chronic disease, (c) perimenopausal and menopausal-related hormonal treatment timing effects on the development and onset of ADRD, (d) the influence of chronic disease (i.e., T2DM, AH, and related CVD comorbidities) on the development and onset of ADRD, and (e) an early detection or warning diagnosing system that could predict or point to the early modifiable risk factors for the prevalence, development and onset of ADRD at the population and individual levels.

The findings from this study may help public health researchers and practitioners to better understand the potential associations between ADRD, SDoH, and chronic disease in the United States. With this understanding, they may be able to devise contextual and culturally sensitive public health strategies to delay and prevent ADRD incorporating the community as the primary stakeholder in the process. These strategies should include sustainable empowerment through human development and economic growth (Dawes, 2020).

Problem Statement

The focus of this study was the increased prevalence of ADRD in the United States throughout the past 4 decades. The increase, coupled with the adverse effects of inequalities related to SDoH, represents a public health problem. ADRD prevalence intertwines with SDoH in a spatiotemporal relationship that varies and is, thus, modifiable. In the U.S. context of chronic disease (i.e., T2DM, AH, and related CVD comorbidities), if unattended, ADRD could become the genesis of a disease-poverty conundrum affecting current and future generations of Americans (CDC, 2022; Groeneveld et al., 2018; Li et al., 2022; Mielke, 2018; Pahwa et al., 2021; Rosselli et al., 2022; Schikowski & Altuğ, 2020). In the United States, ADRD affects people from all walks of life, though women bear a two-fold higher risk than men. The neurodegenerative nature of ADRD imposes disproportionately incapacitating health and financial burdens on the patient, family, caregivers, and society, especially in the context of chronic diseases like T2DM and AH, lower income demographics, and related economic minorities.

In the United States, 60% to 70% of all dementia cases are due to AD, and these cases are projected to rise to 14 to 16 million by 2050 (Mielke, 2018). The two-fold higher risk for ADRD among women compared to men is often correlated to the physiological and psychological changes that women undergo throughout their lives, especially around the age of menopause, and that have similar pathophysiologic mechanisms (i.e., low-chronic inflammation) to T2DM, AH, CVD, rheumatoid arthritis (RA), and menopause physiological changes (Groeneveld et al., 2018; Mielke, 2018;

Pahwa et al., 2021; Rosselli et al., 2022; Schikowski & Altuğ, 2020). These effects are exacerbated by modifiable risk factors related to SDoH that often disproportionately affect lower income demographics and related economic minorities in a seemingly spatiotemporal relationship between ADRD, T2DM, CVD, and the sociopolitical and environmentally imposed SDoH, and observed to vary spatiotemporally. The SDoH framework is useful for approaching the related public health problems and impairment of economic growth and human development arising from these conditions (Bhunia & Shit, 2019; CDC, 2022).

Purpose of the Study

In this quantitative cross-sectional study, I evaluated the association between ADRD prevalence (dependent variable) and SDoH (namely, educational attainment, income, housing, and pollution) in the U.S. context of T2DM and AH (as predictor variables). For this analysis, health and sociodemographic information at the U.S. county level (the unit of analysis) were obtained from the 2018 U.S. County Health Rankings & Roadmaps (CHR&R, 2023) and the Centers for Medicare & Medicaid Services' (CMS) multiple chronic diseases (CMS, 2018) secondary data sets. The data sets were geospatially joined (coded by county) using geographical information systems (GIS) software (ArcGIS Online and ArcGIS Pro 3.2) for statistical evaluation. Some of the variables at the county population level (unit of analysis) included the prevalence of ADRD, T2DM, and AH. The data also contained population percentages of diabetics, women, and adults over 65, and other sociodemographic measures related to SDoH (e.g., education attainment and housing cost). The statistical analysis included mapping the

geospatial distribution of ADRD, T2DM, AH, and related CVD comorbidities in the context of influencing SDoH and their corresponding hotspot analysis at 95% CI, p <0.05. Moreover, geographically weighted regression (GWR) and multiscale geographically weighted regression (MGWR) statistical analyses, at 95% CI, p <0.05, were employed to identify whether any statistically significant associations existed between the prevalence of ADRD and SDoH, T2DM, and AH in the United States.

Research Questions and Hypotheses

This study seeks to identify statistically significant associations between the prevalence of ADRD and SDoH in the U.S. context of T2DM. To these effects, ADRD prevalence, the outcome variable, is measured as a percentage of each U.S. county population. The exact population level of measurements is applied to the independent predictor variables SDoH (educational attainment, income, housing, and pollution) and the prevalence of T2DM and AH in the United States. Hence, the following RQs are postulated:

RQ1: Is there a statistically significant predictable relationship exist between SDoH (education attainment, income, housing, and pollution) and the prevalence of ADRD in the United States?

$H_0$1: No, there is no statistically significant predictable relationship between SDoH (education attainment, income, housing, and pollution) and the prevalence of ADRD in the United States.

H_a1: Yes, there is a statistically significant predictable relationship between SDoH (education attainment, income, housing, and pollution) and the prevalence of ADRD in the United States.

RQ2: Is there a statistically significant predictable statistical relationship exist between T2DM and the prevalence of ADRD in the United States?

H_02: No, there is no statistically significant predictable relationship between T2DM and the prevalence of ADRD in the United States.

H_a2: Yes, there is a statistically significant predictable relationship between T2DM and the prevalence of ADRD in the United States.

RQ3: Is there a statistically significant predictable relationship exist between AH and the prevalence of ADRD in the United States?

H_03: No, there is no statistically significant predictable relationship between AH and the prevalence of ADRD in the United States.

H_a3: Yes, there is a statistically significant statistically predictable relationship between AH and the prevalence of ADRD in the United States.

RQ4: Is there a statistically significant predictable relationship exist between SDoH (education attainment, income, housing, and pollution) and the prevalence of ADRD in the U.S. context of T2DM and AH?

H_04: No, there is no statistically significant predictable relationship between SDoH (education attainment, income, housing, and pollution) and the prevalence of ADRD in the U.S. context of T2DM and AH.

H_a4: Yes, there is a statistically significant predictable relationship between SDoH (education attainment, income, housing, and pollution) and the prevalence of ADRD in the U.S. context of T2DM and AH.

Theoretical Foundation for the Study

The theoretical framework grounding this study was the SDoH framework (CDC, 2022). The logical associations between this study's framework and its nature include the research evaluation of SDoH (namely, education attainment, income, housing, and pollution) as modifiable risk factors and potential early predictors for ADRD prevalence in the U.S. context of T2DM and AH at the county population level (unit of analysis). From a systems-thinking perspective, I examined the problem using the five interrelated domains of the SDoH framework. The CDC (2022) indicated that the SDoH entails all nonmedical factors affecting health dynamics and related outcomes, thus including the sociopolitical settings in which people are born, grow, work, live, and age, alongside the natural and built environment, and the socioeconomics and social-political constructs that shape and condition daily life (see Figure 1; CDC, 2022).

This system-of-systems view entails the search for sustainable and balanced promotion, with equal access, of opportunities for human development with related economic growth for communities. Moreover, this approach also seeks to empower women as a preventive measure to the increased ADRD prevalence, development, and onset based on contextual SDoH assumed modifiable predictors (Benet, 2013; Bhunia & Shit, 2019; Ettman et al., 2021; Farmer et al., 2013; Thakur et al., 2020; Vrijsen et al., 2021; Yearby, 2018).

Figure 1

The Influence of the Social Determinants of Health on Alzheimer's Disease and Related Dementias

Note. The figure illustrates how the social determinants of health and political precursors cumulatively affect and govern human health dynamics and related outcomes for Alzheimer's disease and related dementias. Adapted from *Social Determinants of Health at CDC*, by Centers for Disease Control and Prevention, 2022b (https://www.cdc.gov/about/sdoh/index.html). In the public domain.

This integral perspective aims to equip individuals, families, communities, and society by empowering communities through women, herein recognized as the primary pillar of the family, the unit cell of society, through awareness and education to catalyze human development with related economic growth in a circular economy approach from within the community, thus promoting better health dynamics and related outcomes through empowerment, equal participation, and representation of the ethnocultural and socioeconomic diversity contextually coexisting and influenced by upstream SDoH as modifiable risk factors of disease outcome (Beatley & Manning, 1997; Benet, 2013;

Bhunia & Shit, 2019; Dawes, 2020; Farmer et al., 2013; Hayden, 1997; Walden University, 2023). Chapter 2 in this dissertation will further explain this rationale and relationships.

Nature of the Study

This quantitative study uses a cross-sectional research design (Burkholder et al., 2019; Cataldo et al., 2019; Frankfort-Nachmias et al., 2019; Lau, 2017; Setia, 2016) to evaluate the influence of SDoH (educational attainment, income, housing, and pollution) on the prevalence, development, and onset of ADRD in the United States in the context of T2DM, AH, and related CVD comorbidities.

The rationale for the focus on these four determinants is that in an open market economy as that of the United States, access to and quality of health care depends on the status and level of employment, often determined by educational attainment and sheltered by the physical and financial security of home ownership, all directly and indirectly affected by the ecotoxicity of environmental pollution affecting the natural and built environment in a geo-temporal relationship that can be evaluated through the five domains of the SDoH framework (education access and quality, health care access and quality, neighborhood and built environment, social and community context, and economic stability (Assari, 2018; Bhunia & Shit, 2019; CDC, 2022; Ettman et al., 2021; Farmer et al., 2013; Picard et al., 2022; Tamang et al., 2014; Thakur et al., 2020).

This quantitative study should help identify potential link(s) of SDoH as modifiable risk factors for the prevalence, development, and onset of ADRD in the United States in the context of T2DM, AH, and related CVD comorbidities. To these

effects, U.S. county (the unit of analysis) population level from the combined secondary data sets of 2018 CHR&R (CHR&R, 2023) and multiple chronic diseases (CMS, 2018) will be statistically evaluated via spatial analysis software using ArcGIS Online, ArcGIS Pro 3.2, and MGWR 2.2 from the Spatial Analysis Research Center (SPARC) of the Arizona State University (ASU) for the associations of ADRD prevalence and SDoH (educational attainment, income, housing, and pollution) in the United States in the context of T2DM, AH, and related CVD comorbidities of using multiple linear regression (MLR), GWR, and MGWR. Thus, it seeks to identify meaningful and statistically significant associations between the prevalence of ADRD and SDoH, T2DM, and AH in the United States (95%CI, $p<0.05$).

Some of the variables at the county population level (unit of analysis) include the prevalence of ADRD, T2DM, and AH. It also contains population percentages of diabetics, females, and adults > 65 and other socio-demographic measures related to SDoH (i.e., education attainment and housing cost).

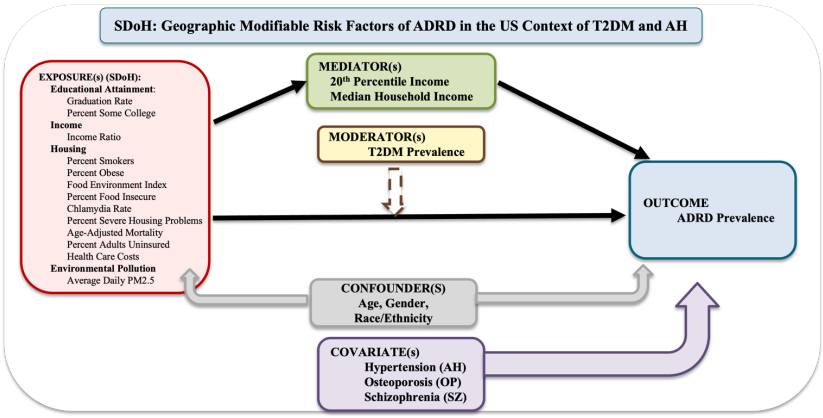
The rationale for the proposed study evaluates SDoH (educational attainment, income, housing, and pollution) as modifiable risk factors for the prevalence, development, and onset of ADRD, pondering the SDoH as spatiotemporal varying relationships. This approach proceeds from the understanding that in an open market economy like the United States. Access to quality education, health care infrastructure, and services depends on socioeconomic aspects governed by income stratification social constructs. As such, education attainment in this society determines the opportunities for human development and economic growth of individuals and their dependents and

related limitations to their natural and built environments. These opportunity limitations include income, access to health care insurance, infrastructure and services, further education, housing, and income generation related to employment level, status, and opportunities. To these effects, Majoka & Schimming (2021), Röhr (2021), and Vega et al. (2017) coincide that SDoH, which also entails the contextual forces and systems that govern people's daily life conditions and related human health dynamics and outcomes, are modifiable risk factors for the development and onset of ADRD.

Hence, the nature of this study recognizes SDoH, T2DM, AH, and related CVD comorbidities as modifiable risk factors, contemplates the possible predictable relationship that might exist between ADRD's development, onset, and prevalence with contextually found SDoH, T2DM, AH (see Figure 2), as an early detection system that could help delay or even prevent the development and onset of ADRD empowering communities, through women and from ealy ages, to attain the maximum potential of their human development and economic growth with equality of access to quality education and health care infrastructure and services.

Figure 2

Diagram of Modelling the relationships between contextually found SDoH and ADRD Prevalence in the US context of T2DM and AH. Adapted from Field-Fote et al. (2019).



Definitions

The following definitions are employed throughout this study:

ADRD Prevalence (Outcome Variable): The number of cases of ADRD, including (AD; VD; Lewy body dementia; and frontotemporal, mixed, and reversible dementias) (CDC, 2019; 2023a; Kumar et al., 2014; NIH, 2023) during a particular interval of time and in a specific population. It is often expressed per 1,000 people during a year or as a percentage of the total observed population in a time interval. In this study, ADRD prevalence is evaluated for 2018. ADRD prevalence, concerning the specified exposures and related confounders, mediators, moderators, and covariates, is the outcome measure that this study will geospatially evaluate under the SDoH framework (Bhunia & Shit, 2019; CDC, 2019; 2022; National Institute of Aging [NIA], 2021; 2023).

Alzheimer's Disease and Related Dementias (ADRD): A conglomerate of neurodegenerative, thus far uncurable, dementia-causing diseases including AD; VD;

Lewy body dementia; and frontotemporal, mixed, and reversible dementias (CDC, 2019; Kumar et al., 2014; NIH, 2023). AD is the most commonly observed neurodegenerative disease-causing dementia. It entails anomalous concentrations of amyloid plaques and tau tangles proteins throughout the brain. Often classified as mild, moderate, and severe, it affects memory, cognitive and motor-control abilities. This type of disease is most often observed in adults >60, yet early onset has been diagnosed in adults >30 (NIA, 2023),

Frontotemporal dementia entails accumulating anomalous amounts or forms of tau and TDP-43 proteins in brain neurons' frontal and temporal lobes. Frontotemporal dementia is often characterized by decreased behavioral and emotional intelligence, cognitive (using and understanding language), and motor-cognitive abilities. This type of dementia is most often observed in adults 45-64 (NIA, 2023).

Lewy Body Dementia (LBD): part of the ADRD group of dementias, entails the formation of abnormal alpha-synuclein protein deposits, called Lewy bodies, in the brain tissue. These anomalous deposits alter chemicals in the brain, concatenating functional impairments, including thinking, movement, behavior, and mood. This type of dementia is most often observed in adults >50 (NIA, 2023),

VD entails different conditions in which blood clots truncate blood flow in the brain. T2DM, AH, and high cholesterol are the most significant risk factors for VD development and onset. VD's symptoms vary by size and affect areas of the brain, and they often include memory loss related to current or past events, misplacing items, difficulties or impairment of cognitive functions, hallucinations or delusions, and poor decision-making. VD is characterized by sudden worsening changes of related symptoms

often exacerbated by strokes and related TIA. This type of dementia is most often observed in adults >65 (NIA, 2023).

Mixed dementia (MD) entails simultaneously concurring two or more types of dementias. MD is most often observed in adults >80. MD is not evident in clinical diagnosis due to the similarity or overlapping of symptoms of the most prominent disease over the lesser. However, dementia-related progression in MD patients occurs faster than when only one type of dementia is present (CDC, 2019).

Exposure/Predictor Variables: Exposures include socioeconomic and health behavior factors (high school [HS] graduation, food environment index(FEI), percentage of adults 25-44 with some college, percentage of women, percentage of people >65, county's health rank, quality of life rank, clinical care rank, and life length rank) corresponding to the imposed burdens known or suspected of contributing to disease development and onset.

Educational attainment (Exposure/Predictor Variable): Refers to the maximum achieved instructional education measured in schooling years or the highest degree attained. This study uses the HS graduation percentage of the county population and population percentage 25-44 with some post-secondary education who have not achieved a post-secondary degree. Here, the latter group represents much of the economically active population and are often found to be heads of households.

Housing (Exposure/Predictor Variable): This study refers to housing or housing status as the percentage of the population with severe housing problems and the percentage of people with high housing costs >50% of their income.

Environmental Pollution PM2.5 (Exposure/Predictor Variable): This study employs the maximum allowable amount of particulate matter with an aerodynamic diameter of <2.5 μm. PM2.5 exposures have often been related to adverse health outcomes (i.e., CVD, asthma, AH, T2DM, and ADRD). Hence, PM2.5 levels are regulated globally. In the United States, the U.S. Environmental Protection Agency regulates PM2.5 standards adhering to the National Ambient Air Quality Standards regarding indoor air quality by specifying the maximum amount of PM2.5 in outdoor air by activity (Di Fonzo et al., 2022).

Income (Mediator Variable): Whether attained from work (wages) or via governmental subsidy, represents a modifier in the outcome-predictors association, especially when evaluating people in poverty or with the 20th percentile of income. To these effects, income represents the buying power and hence the ability to access quality, education, housing, and health care infrastructure and services. Income varies with age, and gender depending on educational attainment and level of employment. Household Income and 20th Percentile Income are considered mediators, for they are included in the exposure-outcome pathway of association, varying the effect of exposure and related outcome. This dissertation employs the percentage of population at or below the U.S. household median income and 20th percentile income measurements.

Type 2 Diabetes Mellitus (T2DM) (Moderator Variable): Diabetes mellitus is a life-course chronic disease involving a deficient and autoimmune response to either the production or use of insulin in cell metabolism needed to convert foods into glucose to fuel the energy needed to carry out essential life functions and work (CDC, 2023a).

T2DM, on the other hand, is often related to lifestyles, autoimmune, and environmental factors, and it is not yet well-understood pathogenesis has led to the inclusion of metabolic syndrome (MetS), latent autoimmune diabetes in adults, and insulin resistance, all related to concurring comorbidities such as CVD, rheumatoid arthritis (RA), AH, ADRD and even hormonal dysregulation due to pre-menopause, menopause, and postmenopause physiological changes, all involving subjacent pathophysiological mechanism of low-chronic inflammation. T2DM is a moderator because it's gravity and related comorbidities (i.e., CVD and AH) emanating from its relation to the outcome affect the outcome and related prognosis of ADRD (Banerjee & Bytyci, 2016; Buzzetti et al. 2020; Carlsson, 2019; CDC, 2023a; Cousminer et al. 2018; Jones et al. 2021; Mancusi et al., 2020; Mishra et al. 2018; Pahwa, 2021; Pozzilli & & Pieralice, 2018; Scheyer et al. 2018; Sun et al., 2019; Wang, 2020).

Arterial Hypertension (AH) Prevalence (Covariate): AH is the clinical condition of living with high blood pressure > 140/90 mmHg (CDC, 2021). "Covariate" (AH prevalence) refers to a CVD comorbidity that often accompanies T2DM but whose correlation is not related to the exposure-outcome association. It helps predict the outcome, for it is often found in T2DM. This co-variability of AH is likely associated with the burden of unhealthy behaviors, malnourishment, reduced physical activity, and medication treatments using glucocorticoids, insulin, and antihypertensives accounting only for modifiable factors and not genetic load (Rayner et al., 2019).

Schizophrenia (SZ) entails a mental disorder often characterized by psychotic episodes that impact motor and cognitive abilities, reality perceptions, and emotional and

social responsiveness. Although a treatable condition, SZ's impact on cognitive abilities is often diagnosed from an early age (typically from late adolescence). SZ is a protracted condition and can be severe and disabling. While SZ is not a form of dementia, SZ patients have an elevated risk of developing AD. SZ and AD have been correlated by their similarities in white matter anomalies and cognitive shortfalls as characteristics of these diseases. In the United States, SZ prevalence ranges between 0.25% and 0.64% (National Institute of Mental Health, n.d.; de Oliveira-Souza et al., 2007; Kochunov et al., 2021).

Osteoporosis (OP) is a medical condition characterized by bone density and microarchitecture degradation, thus making the bone less dense, weak, and brittle with a higher propensity to fracture. OP has been correlated to CVD, AH, and ADRD due to the calcification of vessels often promoting VD (Başgöz et al., 2022; Lary et al., 2021; Polyzos et al., 2021; Zhang et al., 2022).

Age, Gender, and Ethnicity (Confounder Variables): age, gender, and ethnicity are commonly encountered confounder variables in epidemiology because they variably influence the exposures and outcomes throughout their different strata measured through the population percentages correlating to the health care domain with transversal effects throughout all five SDoH domains. This study considers age, gender, and ethnicity as confounders, based on data availability, and controls for their effects through a MLR analysis. On the other hand, the GWR and MGWR include these variables as predictors, taking two-dimensional multifactorial measurements in a geo-temporal varying relationship.

ArcGIS Online: Online Geographical Information Systems mapping and statistical software (ArcGIS Online, n.d.a).

ArcGIS Pro 3.2: Desktop Geographical Information Systems mapping and statistical software (ArcGIS Pro, n.d.b).

Geographically Weighted Regression (GWR): Local statistical regression model that assumes that spatial-varying relationships happen at a constant rate of change with respect to distance. GWR also assumes that the strength of an outcome-predictor relationship decreases as the distance between comparison points increases (Bhunia & Shit, 2019; de Smith et al., 2018).

Gettis-Ord Gi* statistic: a ratio of the total of the values in a specified area to the global total. It calculates a Z-score and p-value for each spatial analysis unit (statistical significance $p < .01$) (Bhunia & Shit, 2019; de Smith et al., 2018).

Geospatial Distribution: The distribution or allocation of spatially varying relationship values or attributes attached to a corresponding geo-code or coordinate (Bhunia & Shit, 2019; de Smith et al., 2018).

Hot Spot Analysis: Hot Spot analysis calculates the Getis-Ord Gi* statistic. This computation entails the identification of the highest and lowest values for each feature of the data set. It identifies where these cluster spatially using the resultant z-scores and p-values (de Smith et al., 2018)

MGWR 2.2: GWR and MGWR statistical modeling software from the SPARC of ASU (n,d.).

Multiscale Geographically Weighted Regression (MGWR): Local statistical regression model that refines the GWR model as it decreases the statistical error (SE). MGWR assumes that spatial-varying relationships happen at a non-constant rate of change with respect to distance. MGWR also assumes that the strength of an outcome-predictor relationship decreases as the distance between comparison points increases.

Social Determinants of Health Inequalities (SDoH): Conceptual framework that entails all nonmedical factors affecting health dynamics and related outcomes, thus including the socio-political settings in which people are born, grow, work, live, and age, alongside the natural and built environment and the socioeconomics and social-political constructs that shape and condition daily life (CDC, 2022).

Assumptions

This study uses secondary data captured and curated by the U.S. government and related servicing agencies. Hence, this study assumes that the employed data set is a nationally representative sample at the county and state levels. Thus, any findings and conclusions drawn from the analyses can be contextually applied to the general population.

Moreover, this study assumes that the adverse effects of contextually found SDoH (educational attainment, income, housing, and pollution) are cumulative and additive. Where longer and sustained exposures would lead to greater odds of worse health outcomes. To these effects, this study assumes that the reported educational attainment of the population has been obtained earlier in life: <20 for HS, <25 for college, <35 for graduate, and <40 for any post-graduate degree. This assumption integrates the

cumulative influence of contextually found SDoH on educational attainment and the risk for ADRD, prevalence, development, and onset, to which most available literature points to a resilience if not protective, effect against cognitive decline. However, the literature needs to clarify whether the time of highest educational attainment increases or diminishes such attributed protective effect against cognitive decline. Nor is it clear how contextual SDoH influence the educational attainment-cognitive decline association. Hence, it is also assumed that this dissertation's cross-sectional design and proposed statistical analyses were the best possible theory-grounded mechanisms and tools to address the established RQs and related hypotheses.

Scope and Delimitations

In this study, I analyzed spatially joined secondary data sets from the 2018 U.S. CHR&R (CHR&R, 2023) and the 2018 multiple chronic diseases from the CMS (CMS, 2018), seeking to identify potential links between SDoH, as modifiable risk factors, and the prevalence, development, and onset of ADRD in the U.S. context of chronic disease (namely, T2DM and AH). These associations have been chosen because they represent an understudied area in the available scientific literature. Moreover, should there be a meaningful and statistically significant association between ADRD and SDoH, the latter could potentially represent early predictors of the disease outcome, which, evaluated at the population level, would inform community stakeholders and related decision-makers for the integral implementation of culturally sensitive and contextual public policies. Thus, this study's unit of analysis is the U.S. county population for 2017-2018, as collected by CHR&R (2023) and CMS (2018).

MLR based on ordinary least squares (OLS), GWR, and MGWR will be employed to statistically (95%CI, $p<0.05$) evaluate the association of ADRD prevalence and SDoH (educational attainment, income, housing, and pollution) in the United States in the context of T2DM, AH, and related CVD comorbidities seeking to identify meaningful and statistically significant associations between the prevalence of ADRD and SDoH, T2DM, and AH in the United States.

Moreover, GWR and MGWR represent the best statistical modeling analysis techniques for spatial and temporal varying predictor-outcome relationships, allowing for enhanced local regressions, which more accurately identify the sought relationships and related predictor effects on a specific outcome. This characteristic of the analysis is a critical advantage that would serve to better inform contextual decision-making associated processes and stakeholders, from the community to their government, at the local and national levels, hence making this approach replicable in other spatiotemporal socioeconomic and cultural settings to identify their related trends in those areas (Bhunia & Shit, 2019; Fotheringham et al., 2003; Fotheringham et al., 2017; Yu et al., 2020)

Limitations

This study presents some limitations. The data sets provide population-level information at the county level for the United States. Hence, the cross-sectional design. To these effects, the 2018 CMS and CHR&R data sets are secondary data collected and curated by the U.S. government and related service agencies. Hence, the variables and information provided are predetermined by their regulations and requirements and not by my request as a researcher, which aims to avoid biases and external validity issues as the

researcher is not involved in data selection or collection methods and mechanisms. Therefore, the proposed design and statistical analysis are performed at the U.S. county-level population (unit of analysis) under the SDoH framework.

This study focuses on the association between 2018 ADRD prevalence and SDoH (educational attainment, income, housing, and pollution) in the U.S. context of chronic diseases, namely, T2DM) and AH, two of the often ADRD-related comorbidities and leading causes of death in the United States. Elucidating the associations between ADRD and SDoH influencing chronic disease could provide enhanced avenues of research not just on the underlying pathophysiological mechanisms of ADRD and comorbidities (i.e., low-chronic inflammation) and the imposed adverse effects of SDoH on these associations. Hence, the literature review in this study will address ADRD, which includes AD; VD; Lewy body dementia; and frontotemporal, mixed, and reversible dementias (CDC, 2019; Kumar et al., 2014; NIH, 2023), understanding that although familial history, genetic, and nuclear imaging testing are conjugated in the diagnosis and prognosis of dementia causes, to date, AD, related brain, and other neuropathologies can only be accurately and conclusively diagnosed through autopsy analysis of post-mortem brain tissue. Thus, autopsy analyses remain the gold standard for a conclusive dementia diagnosis. (Elder et al., 2019; Suemoto & Leite, 2023). To these effects, the literature review will further address some of the underlying mechanisms of how ADRD prevalence intertwines with SDoH in a spatiotemporal varying yet modifiable relationship, which, if unattended, could become the genesis of a disease-poverty conundrum affecting current and future generations of Americans. The rationale behind

this analysis is that if there are meaningful and statistically significant relationships between ADRD prevalence and contextual SDoH in the presence or absence of chronic comorbidities, these relationships could serve as early predictors of disease outcome. This approach aims to inform and empower the community in the decision-making processes of the strategies needed to be implemented to address the burdens imposed by SDoH.

Significance

This study is significant in that it addresses the influence of SDoH (educational attainment, income, housing, and pollution) as modifiable risk factors for reducing ADRD prevalence, development, and onset in the U.S. context of chronic disease from the county and related community population level. This investigation will be conducted from a systems-thinking approach. Thus, each component of the SDoH framework is considered an optimizable subsystem to help understand the contextual influence of SDoH on human health dynamics and related outcomes that affect the individual, interpersonal, and community settings. From that perspective, educational attainment, income, housing, and pollution are also intricately related to the community's diversity of beliefs and practices that further influence health dynamics and outcomes. Thus, SDoH could represent early contextual predictors of specific disease outcomes. Hence, these SDoH can be assumed to become optimizable subsystems of these relationships.

Public Health and Epidemiology

In this dissertation, I evaluate SDoH (educational attainment, income, housing, and pollution) as modifiable risk factors for ADRD prevalence in the U.S. context of

chronic disease (T2DM and AH) at the U.S. county population level. As such, the contribution of this study seeks to catalyze a paradigm shift in public health such that politics and public policy will be based on and governed by public health and scientific knowledge and evidence. This study aims to stimulate a sustainable approach to positive social change by promoting human development with related economic growth in a circular economy strategy that promotes equal access to quality health care, educational infrastructure, and services. These objectives align with the 2030 Agenda and related Sustainable Development Goals (United Nations, 2015, 2023) and are based on the fundamental role that educational attainment has in an open market and globalized economic system. A system that often disproportionately limits human development and economic growth, especially on lower income demographics and related economic minorities, based on social and political constructs of class and income stratification.

Research

Considering the thus far identified gaps that include (a) the influence of SDoH on the prevalence of ADRD in the population and its development and onset at the individual levels, (b) perimenopausal and menopausal-related hormonal treatment timing effects on the development and onset of ADRD, (c) the influence of chronic disease (i.e., T2DM and related CVD comorbidities) on the development and onset of ADRD, (d) the geo-temporal relationship effects of exposures (SDoH and related environmental pollution) and ADRD in the context of chronic disease, and (e) an early detection or warning diagnosing system that could predict or point to the early modifiable risk factors for the development and onset of ADRD at the population and individual levels. Where,

all five factors are believed to significantly influence the prevalence, development, and onset of ADRD at the population and individual levels (Bhunia & Shit, 2019; CDC, 2019; 2022; Fotheringham et al., 2003; Fotheringham et al., 2017; Groeneveld et al., 2018; Love & Miners, 2016; Mielke, 2018; NIA, 2021; 2023; Picard et al., 2022; Schikowski & Altuğ, 2020; Tamang et al., 2014; Yu et al., 2020). This dissertation will evaluate SDoH (education attainment, income, housing, and pollution) representing increased risks for the prevalence, development, and onset of ADRD and related cognitive decline and impairment in the United States at the county-level population. Moreover, this dissertation will also evaluate the extent to which T2DM and related AH represent increased risks for the prevalence, development, and onset of ADRD in the United States. Hence, the anticipated new knowledge would include a predictable and optimizable statistically significant model of the adverse influence of SDoH on the increase in prevalence and risk for the development and onset of ADRD in the United States.

Positive Social Change

This dissertation seeks a predictable and, therefore, optimizable contextually based relationship between SDoH T2DM and AH with the increased prevalence of ADRD in the United States. The herein proposed geographically weighted statistical modeling approach would elicit the evaluation of spatial and temporal relationships of contextual SDoH, chronic diseases (T2DM, AH, and related CVD), on the prevalence, development, and onset of ADRD. Thus, this approach seeks to render new avenues of research on the imposed burdens by SDoH. I also expect this study to catalyze a

sustainable approach to positive social change based on awareness and education promoting human development and related economic growth from within the community. In a circular economy approach, it would reinvest in the community's social, economic, and natural resources.

The confirmation of predictable and, therefore, optimizable relationships between SDoH, T2DM, and AH with the prevalence, development, and onset of ADRD would help with the justification, development, and implementation of new public health strategies based on community-based participatory research to learn, understand and engage the contextual factors influencing the community regarding these health outcomes. As such, the expected new knowledge would help catalyze a sustainable approach to positive social change that reinvests in the community's social capital through a circular economy model. Thus promoting human development with economic growth, belongingness, and the community's ownership of their contextual problems through the empowerment of women, considered the fundamental pillar of the family, the unit cell of society, and the critical bridge for the ongoing generational gap between the young and the elderly For all described above, the potential relationships between ADRD and SDoH, T2DM, AH, and related CVD comorbidities warrant the herein-proposed investigation.

Summary

The prevalence of ADRD shows a sustained increase in the United States throughout the past 4 decades. These neurodegenerative and dementia-causing outcomes, coupled with the adverse effects of SDoH, represent a public health problem that society

must address. ADRD prevalence intertwines with SDoH in a spatiotemporal varying relationship, which, if unattended, could become the genesis of a disease-poverty conundrum affecting current and future generations of Americans.

Dementia is not part of the normal aging process, remains uncurable, and its related pathogenesis can only be accurately diagnosed through autopsy. Currently, familial, clinical history and some genetic biomarkers testing enable medical practitioners to diagnose and treat dementia based on clinical symptoms. Among ADRD are AD; VD; Lewy body dementia; and frontotemporal, mixed, and reversible dementias. Although dementia is most often observed in adults >65, it is not a part of a normal aging process. Instead, it entails a combination of effects between genetic load and the cumulative adverse influence of contextually found SDoH.

AD accounts for 60% to 70% of dementia cases in the United States, and the CDC projected a three-fold increase in the incidence of AD over the next 4 decades. Moreover, females have a two-fold risk than males for the development and onset of ADRD solely based on gender and related physiological and psychological changes women undergo throughout their lives. Throughout ethnocultural and socioeconomic spectrums of human history, women represent, if not the fundamental pillar of the family, society's fundamental unit.

To these effects, the SDoH entail all nonmedical factors affecting health dynamics and related outcomes, thus including the socio-political settings in which people are born, grow, work, live, and age, alongside the natural and built environment and the socioeconomics and social-political constructs that shape and condition daily life (CDC,

2022). Hence, it is crucial to recognize, evaluate, and address the spatiotemporal cumulative adverse effects of contextually found SDoH on human health outcomes like ADRD, related human development, and economic growth.

It is, therefore, crucial to identify potential statistically significant predicting relationships between ADRD prevalence, development, and onset with SDoH that would help inform the decision-making processes to reduce the burdens imposed by SDoH on human health dynamic and related outcomes (ADRD), which disproportionately limit human-development and related economic growth on lower income demographics and related economic minorities, especially in the context of chronic comorbidities, in the United States and globally.

For all described above, the potential relationships between ADRD and SDoH, in the U.S. context of T2DM, AH, and related CVD comorbidities warrant the herein-proposed investigation. To these effects, Chapter 2 will follow to continue developing this dissertation, including the strategies for relevant literature review, the theoretical framework grounding this dissertation, relevant concepts, the analysis of the found relative scientific literature for outcome-predictor variables to evaluate the association ADRD and SDoH in the U.S. context of T2DM and AH; and a chapter summary.

Chapter 2: Literature Review

Introduction

The sustained increase in the prevalence of ADRD in the United States throughout the past 4 decades, coupled with the adverse effects of contextual SDoH, represents a public health problem. SDoH impose health and financial burdens that shape human health dynamics and related disease outcomes. SDoH disproportionately affect lower income demographics and related economic minorities, especially in the context of existing chronic comorbidities (i.e., T2DM and AH, CDC,2022). From this perspective, ADRD prevalence, development, and onset intertwine with contextually found SDoH in a spatiotemporal varying relationship, which, if unattended, could become the genesis of a disease-poverty conundrum affecting current and future generations of Americans. I evaluated the association between ADRD prevalence and SDoH (namely, educational attainment, income, housing, and pollution) in the U.S. context of T2DM and AH.

Dementia is the most common outcome of ADRD, a conglomerate of thus far uncurable neurodegenerative diseases that progressively concatenate in cognitive and motor control impairment and, subsequently, dementia, most often signaled by memory loss. The neurodegenerative nature of ADRD disproportionately imposes incapacitating health and financial burdens on the patient, family, caregivers, and society, especially in chronic disease (i.e., T2DM and AH), lower income demographics, and related economic minorities (AA, 2020; CDC, 2022). Although dementia is most often observed in adults over the age of 65, it is not a part of a normal aging process. Instead, it entails a combination of effects between genetic load and the cumulative adverse influence of

contextually found SDoH (AA, 2020; CDC, 2022; Kumar et al., 2014). Among ADRD are AD; VD; Lewy body dementia; and frontotemporal, mixed, and reversible dementias (CDC, 2019; Kumar et al., 2014; NIH, 2023). Of these dementia-causing diseases, AD is the most common, representing more than 60% of cases in the United States. Although ADRD affect people from all walks of life in the United States, women bear a two-fold higher risk than men, based solely on their gender and related physiological changes women undergo throughout their lives (Melke, 2018).

In this quantitative cross-sectional study, I evaluated the influence of SDoH (educational attainment, income, housing, and pollution) on the prevalence, development, and onset of ADRD in the U.S. context of T2DM, AH, and related CVD comorbidities. Elucidating potential link(s) between the prevalence, development, and onset of ADRD and contextually found SDoH may render statistically significant and meaningful associations at the population level that could open new avenues of research at the individual level for ADRD. Due to these effects, SDoH are recognized as modifiable risk factors for disease outcomes (CDC, 2022).

The SDoH conceptual framework entails a wide array of socioeconomic and politically related factors that relate all nonmedical factors governing health dynamics and related outcomes, thus including the sociopolitical settings in which people are born, grow, work, live, and age, alongside the natural and built environment and the socioeconomics and sociopolitical constructs that shape and condition daily life (CDC, 2022). This dissertation focused on educational attainment, income, housing, and pollution as upstream SDoH affecting ADRD prevalence, development, and onset. This

research pondered the intricate relationship among these SDoH (educational attainment, income, housing, and pollution) as modifiable risk factors for disease outcomes. In a globalized and ever-competitive, open market economy like the United States, access to and quality health care depends on the status and level of employment and related income-generating capacity. These conditions are often determined by educational attainment and sheltered by the physical and financial security of home ownership, all directly and indirectly affected by the ecotoxicity of environmental pollution affecting the natural and built environment in a spatiotemporal relationship (Assari, 2018; Bhunia & Shit, 2019; Ettman et al., 2021; Farmer et al., 2013; Picard et al., 2022; Tamang et al., 2014; Thakur et al., 2020). The effects of an open market globalized economy were evident in the inequities and inequalities of disease burden and related COVID-19 vaccine production and distribution through the pandemic. Due to supply chain production and logistic problems, more prosperous economies obtained their vaccines faster than lower-income countries (Abrams & Szefler, 2020; Raj et al., 2022).

In this chapter, I evaluate the available literature and corresponding identified gaps. The chapter includes discussion of the literature search strategy, theoretical framework, and pertinent concepts to understand the association between ADRD prevalence, development, and onset with SDoH (educational, attainment, income, housing, and pollution) in the U.S. context of T2DM and AH. I also evaluate the available literature on ADRD prevalence, development, and onset and the established SDoH as potential predictor variables to this outcome.

Literature Search Strategy

In reviewing the available literature on the research topic, I sought relevant studies concerning potential associations between ADRD prevalence, development, and onset with the established SDoH (educational attainment, income, housing, and pollution). The review includes literature concerning geospatial analysis and the association between T2DM, AH, menopause, and ADRD prevalence, development, and onset. The rationale for this literature review strategy was that contextual SDoH govern human health dynamics and related outcomes, disproportionately affecting lower income demographics and related economic minorities (CDC, 2022). The cumulative effects of such health and financial burden could correlate to ADRD prevalence, development, and onset. Thus, a predictive statistical model could be developed at the county population level.

I searched ProQuest Global (English, Spanish, Portuguese, French, and Italian) and ProQuest Walden for PhD dissertations and EBSCO databases for peer-reviewed scholarly articles from the Walden University Library. My focus was relevant seminal and recent scientific articles from the last 5 years. Whenever little or no available scientific literature was found relevant to this dissertation, the search scope was broadened to the Google Scholar search engine using the same Boolean operators and search arguments as in the academic databases. I used several Boolean operators and keywords to focus the search due to the broad aspects of ADRD prevalence, development, and onset related to SDoH in the context of chronic disease (see Table 1).

Table 1

Boolean Search Arguments for ADRD, SDoH, T2DM, AH, and Geospatial Analysis

Search argument	Database		
	ProQuest Dissertations & Theses (Walden)	ProQuest Dissertations & Theses Global (other institutions)	EBSCO
(Alzheimer's disease and related dementias or ADRD) AND (social determinants or SDOH).	3	20	27
(Alzheimer's disease and related dementias or ADRD) AND (educational attainment) AND (social Determinants or SDOH).	1	0	1
(Alzheimer's disease and related dementias or ADRD) AND (educational attainment)	1	1	23
(Alzheimer's disease and related dementias or ADRD) AND (income or poverty) AND (social determinants or SDOH).	0	0	0
(Alzheimer's disease and related dementias or ADRD) AND (income or poverty)	3	7	150
(Alzheimer's disease and related dementias or ADRD) AND (housing or housing status) AND (social determinants or SDOH)	0	0	2
(Alzheimer's disease and related dementias or ADRD) AND (environmental pollution or pollution) AND (social determinants or SDOH).	0	0	0
(Alzheimer's disease and related dementias or ADRD) AND (pollution or pollution)	0	7	68
(Chronic diseases) AND (ADRD or dementia) AND (social determinant or SDOH)	0	2	16
(Alzheimer's disease and related dementias or ADRD) AND (T2DM)	0	0	0

Search argument	Database		
	ProQuest Dissertations & Theses (Walden)	ProQuest Dissertations & Theses Global (other institutions)	EBSCO
AND (social determinants or SDOH)			
(Alzheimer's disease and related dementias or ADRD) AND (T2DM)	0	1	3
(Hypertension) AND (ADRD or Dementia) AND (social determinant or SDOH)	5	5	69
(Alzheimer's disease) AND (social determinants or SDOH)	6	6	111
(Spatial or geospatial) AND (Alzheimer's disease or dementia) AND (social determinant or SDOH)	0	0	6
(Spatial or geospatial) AND (social determinant or SDOH)	0	0	1,228
(Spatial or geospatial) AND (educational attainment or education) AND (social determinants or SDOH)	0	0	16
(Spatial or geospatial) AND (income) AND (social determinants or SDOH)	0	0	168
(Spatial or geospatial) AND (housing) AND (social determinants or SDOH)	0	0	102
(Spatial or geospatial) AND (environmental pollution or pollution) AND (social determinant or SDOH)	0	0	5
(Geospatial analysis) AND (social determinant or SDOH)	5	5	52
(Geographically weighted regression) AND (social determinants)	4	4	0

Note. ADRD = Alzheimer's disease and related dementias; SDoH = social determinants of health; T2DM = type 2 diabetes mellitus; AH = arterial hypertension.

The inclusion/ exclusion search criteria parameters included all the limiting parameters, such as full-text, peer-reviewed scholarly journals, and Ph.D. Dissertations, all written in the past 5 years. The searches were geared to finding the most recent knowledge in the field to inform this dissertation process on SDoH influence on the prevalence, development, and onset of ADRD in the U.S. context of chronic disease and their evaluation from the geospatial perspective.

The found literature addresses dementia and cognitive decline concerning one specific SDoH or aspect at a time. These findings help further point to the gap(s) addressed by my dissertation and inform its process as it is focused and limited to evaluating the association between ADRD prevalence and SDoH (namely, educational attainment, income, housing, and pollution) in the U.S. context of T2DM and AH. This dissertation uses health and socio-demographic information at the U.S. County level (the unit of analysis) from the 2018 U.S. CHR&R (CHR&R, 2023) and the CMS' multiple chronic diseases (CMS, 2018) secondary data sets. This dissertation will use the geo-spatially joined, geo-coded by county (the unit of analysis) of the above combined secondary data sets using GIS software (ArcGIS Online and ArcGIS Pro 3.2), and ASU MGWR 2.2 software for the statistical evaluation and mapping of geospatial relationships between outcome and predictor variables (Bhunia & Shit, 2019; CDC, 2022; Ettman et al., 2021; Farmer et al., 2013; Picard et al., 2022; Tamang et al., 2014; Thakur et al., 2020).

Theoretical Framework

The theoretical framework grounding this study was the SDoH framework. This framework has five domains: (a) education access and quality, (b) health care access and quality, (c) neighborhood and built environment, (d) social and community context, and (e) economic stability (CDC, 2022). Hence, it is crucial to recognize, evaluate, and address the adverse effects of contextually found SDoH as modifiable risk factors for human health dynamics and related outcomes, human development, and related economic growth. The SDoH previously identified by Marmot (2005), Wilkinson & Pickett (2011), Farmer et al. (2013) and expanded upon by Dawes (2020) has been implemented by the WHO and the CDC, whose 2022 conceptualization is employed in this dissertation as has been used in several epidemiologic studies previously (Boakye et al., 2022; Bonzani et al., 2023; Brundon et al., 1998; CDC, 2022; Charlton et al., 2009; de Bellefon & Floch, 2018; Fotheringham et al., 2003; Fotheringham et al., 2017; Kondo, 2015; Iyanda et al., 2020; Oshan et al., 2020; Peters et al., 2021; Raymundo et al., 2021; Rzasa & Ciski, 2022; Tamura et al., 2021; Tiwari & Aljoufie, 2021; Wang et al., 2020; Wood, 2022; Wu et al., 2019). However, no literature has been found to address ADRD prevalence influenced by SDoH in the U.S. context of T2DM and AH. To my knowledge and understanding from the carried-out literature search, this dissertation will be the first study addressing ADRD prevalence, as presented above.

The rationale for the use of the SDoH framework lies on its concept and the socioeconomic U.S. system as follows: The SDoH entail all nonmedical factors affecting health dynamics and related outcomes, thus including the socio-political settings in which

people are born, grow, work, live, and age, alongside the natural and built environment and the socioeconomics and social-political constructs that shape and condition daily life (CDC, 2022). Hence, SDoH correlate to life-long contextually found disparities in disease outcome and related burdens (CDC, 2022; Kondo, 2015; Liu, 2022). Thus, the focus on SDoH because in an open market economy as that of the United States, access to quality housing, education, and health care infrastructure and services depend on socioeconomic status and level related to employment level, often determined by educational attainment and sheltered by the physical and financial security of home ownership, all directly and indirectly affected by the ecotoxicity of environmental pollution affecting the natural and built environment in a geo-temporal relationship that can be evaluated through the five domains of the SDoH framework (Akushevich et al., 2021; Bonzani et al., 2023; Bhunia & Shit, 2019; CDC, 2022; Kondo, 2015; Liu, 2022; Picard et al., 2022; Santamaria-Garcia et al., 2023; Thakur et al., 2020; Walker, 2014).

ADRD entail a conglomerate of neurodegenerative, thus far uncurable, dementia-causing diseases, including AD; VD; Lewy body dementia; and frontotemporal, mixed, and reversible dementias (CDC, 2019; Kumar et al., 2014; NIH, 2023). ADRD prevalence and related development and onset intertwine with the cumulative effects of SDoH in a spatiotemporal varying yet modifiable relationship, which, if unattended, could become the genesis of a disease-poverty conundrum affecting current and future generations of Americans.

Hence, this study focuses on contextually found SDoH (education attainment, income, housing, and pollution) as modifiable risk factors of disease outcome. The

rationale for the focus on these four determinants is that in an open market economy as that of the United States, access to and quality of health care depends on the status and level of employment, often determined by educational attainment and sheltered by the physical and financial security of home ownership, all directly and indirectly affected by the ecotoxicity of environmental pollution affecting the natural and built environment in a geo-temporal relationship that can be evaluated through the five domains of the SDoH framework (education access and quality, health care access and quality, neighborhood and built environment, social and community context, and economic stability; Assari, 2018; Bhunia & Shit, 2019; CDC, 2022; Ettman et al., 2021; Farmer et al., 2013; Picard et al., 2022; Tamang et al., 2014; Thakur et al., 2020).

This dissertation posits a systems-thinking or system-of-systems perspective (Keating et al., 2003; 2021) that will ponder the increased ADRD prevalence public health problem, using the five interrelated domains of the SDoH framework (CDC, 2022). This objective will is approached in a system-of-systems view entails the search for sustainable and balanced health promotion, with equal access, of opportunities for human development with related economic growth for communities by empowering women as a preventive measure to the increased ADRD prevalence, development, and onset, based on the assumed modifiable SDoH (educational attainment, income, housing, and pollution) (Benet, 2013; Bhunia & Shit, 2019; Ettman et al., 2021; Farmer et al., 2013; Keating et al., 2003; 2021; Thakur et al., 2020; Vrijsen et al., 2021; Yearby, 2018).

This integral perspective aims to equip individuals, families, communities, and society by empowering communities through women, herein recognized as the primary

pillar of the family, the unit cell of society, through awareness and education to catalyze human development with related economic growth in a circular economy approach from within the community, thus promoting better health dynamics and related outcomes through empowerment, equal participation, and representation of the ethnocultural and socioeconomic diversity contextually coexisting and influenced by upstream SDoH as modifiable risk factors of disease outcome (Beatley & Manning, 1997; Benet, 2013; Bhunia & Shit, 2019; Dawes, 2020; Farmer et al., 2013; Hayden, 1997; Walden University, 2023).

Literature Review Related to Key Variables and/or Concepts

The available scholarly literature does not address ADRD prevalence as geospatially and contextually influenced by SDoH (educational attainment, income, housing, and pollution) in the U.S. context of chronic disease. Much less from the perspective of an open market economy exacerbating the aforementioned SDoH. However, several scholarly studies regarding ADRD prevalence, development, and onset influenced by a specific SDoH have been reported. Other studies have been written on the use and power of GWR and MGWR compared to OLS-fitted LR models.

Subdivided by concept or variables employed in this dissertation, below is a review of the most relevant scientific literature found regarding this dissertation focus on geographically SDoH (educational attainment, income, housing, and pollution) as modifiable risk factors for ADRD prevalence in the U.S. context of T2DM and AH. Which would be analyzed using GWR, MGWR, and multinomial LR models.

Alzheimer's Disease and Related Dementias as Outcome Variable

The CDC (2019), Kumar et al. (2014), and NIH (2023) established that ADRD entail a group of, thus far, uncurable neurodegenerative diseases whose combination of effects between genetic load and the cumulative adverse influence of contextually found SdoH. Among ADRD are AD; VD; Lewy body dementia; and frontotemporal, mixed, and reversible dementias. Dementia is not a specific disease; it entails a conglomerate of, thus far uncurable, neurodegenerative disorders that progressively concatenate in cognitive and motor control impairment and, subsequently, dementia, often signaled by memory loss. These effects disable people by impairing their proper function at the personal, interpersonal, familial, community, and societal levels.

Although dementia is most often observed in adults >65, it is not a part of a normal aging process. Instead, it entails a combination of effects between genetic load and the cumulative adverse influence of contextually found SdoH. ADRD include AD; VD; Lewy body dementia; and frontotemporal, mixed, and reversible dementias (CDC, 2019; Kumar et al., 2014; NIH, 2023).

In 2018, the CDC informed that ADRD prevalence among people> 65 was 13.8% for non-Hispanic Blacks, 12.2% for Hispanics or Latinos, 10.3% for non-Hispanic Whites, 9.1 % for American Indians and Alaska Natives (AIAN), and 8.4% for Asian and Pacific Islanders. Moreover, the CDC (2018a) pointed out that by 2060, the number of cases of ADRD for non-Hispanic Blacks will grow to approximately 2.2 million and 3.2 million for Hispanics or Latinos. This increase would be partly due to greater longevity and reduced mortality from other chronic diseases (CDC, 2018a).

To these effects, Li et al. (2022) indicated that ADRD prevalence reflects a sustained increase in the United States and globally over the past 4 decades. This increase in prevalence correlates to the cumulative effects of genetic load and contextually found SdoH, viewed herein as modifiable risk factors of disease outcome (CDC, 2022; NIH, 2023). Moreover, Power et al. (2021) found that from 2000 to 2016, ADRD prevalence had increased in the United States, pointing out that lifelong racial disparities related to contextual SdoH (i.e., educational attainment and gender), and chronic diseases such as T2DM and AH), played a significant role. When comparing prevalence variations by race/ethnicity, non-Hispanic Whites showed a prevalence increase from 40% to 44%, yet their related age of onset was delayed on average from 78.2 to 78.7 years. Non-Hispanic Blacks showed a prevalence increase from 37% to 38%, yet their related age of onset was early on average, from 78.0 to 77.9 years for the same period (Power et al., 2021). To these effects, Cortes-Canteli & Iadecola (2020) and Silveira-Rossi et al. (2021) conveyed that atherosclerosis correlates to AH and T2DM interacting through underlying mechanisms of low-chronic inflammation related to MetS, known multicomorbidity contributing factors to the prevalence, development, and onset of ADRD (Beerten et al., 2022; Cortes-Canteli & Iadecola, 2020; Power et al., 2021; Silveira-Rossi et al., 2021).

Furthermore, Rajan et al. (2022) reported that clinical AD risk augments in relation to contextual SdoH and their adverse effects on disease outcomes increase with age. Moreover, Rajan et al. (2022) reported that the 2020 U.S. census-adjusted clinical AD prevalence was 11.3% (95% CI= 10.7, 11.9), where the clinical AD prevalence by race/ethnicity was 18.6% for non-Hispanic Blacks, 14.0% for Hispanics, and 10.0% non-

Hispanic Whites. Moreover, Rajan et al. (2022) estimated that approximately 6.07 million people (95% CI= 5.75, 6.38) live with clinical AD in the United States in 2020 and forecasted a projected growth for 2060 of 13.85 million (95% CI= 12.98, 14.74) Americans. This 2060 clinical AD projected growth would represent a 192% increase in prevalence for non-Hispanic Blacks, 423% for Hispanics, and 63% for non-Hispanic Whites. This projection further pointed out that the increase in prevalence will be more significant with age (>85) and in women.

Thus, from that perspective, the imposed burdens of contextually found upstream SdoH, often disproportionately affecting lower income demographics and related economic minorities, represent a public health problem that society must address. To these effects, ADRD prevalence, development, and onset intertwine with upstream SdoH, which contextually vary in a spatiotemporal yet modifiable relationship, which, if unattended, could become the genesis of a disease-poverty conundrum affecting current and future generations of Americans. Hence, several studies correlate ADRD prevalence, development, and onset to SdoH (i.e., educational attainment, income, housing, pollution, gender, and geographic location) and chronic diseases, such as T2DM and AH, two of the often ADRD-related comorbidities and leading causes of death in the United States (Akushevich et al., 2020; CDC, 2018a; 2022; Groeneveld et al., 2018; Li et al., 2022; Mielke, 2018; Pahwa et al., 2021; Rajan et al; 2022; Rosselli et al., 2022; Schikowski & Altuğ, 2020; Wing et al 2020). Thus, this dissertation focuses on elucidating the associations between ADRD and SdoH in the U.S. context of T2DM and AH.

Social Determinants of Health Inequalities as Predictor Variables

The SDoH framework, with its five domains (education access and quality, health care access and quality, neighborhood and built environment, social and community context, and economic stability; CDC, 2022) grounded this study. The CDC indicated that the SdoH entails all nonmedical factors affecting health dynamics and related outcomes, thus including the socio-political settings in which people are born, grow, work, live, and age, alongside the natural and built environment and the socioeconomics and social-political constructs that shape and condition daily life (CDC, 2022). Hence, SdoH correlate to life-long contextual disparities in dementia risk (Liu, 2022). From this perspective, this study focuses on evaluating the SdoH (namely, education attainment, income, housing, and pollution; see Figure 2) as modifiable risk factors and potential early predictors for the prevalence, development, and onset of ADRD in the U.S. context of T2DM and AH at the county population level (unit of analysis). The rationale for the focus on these four determinants is that in an open market economy as that of the United States, access to and quality of health care depends on the status and level of employment, often determined by educational attainment and sheltered by the physical and financial security of home ownership, all directly and indirectly affected by the ecotoxicity of environmental pollution affecting the natural and built environment in a geo-temporal relationship that can be evaluated through the five domains of the SdoH framework (Akushevich et al., 2021; Assari, 2018; Bonzani et al., 2023; Bhunia & Shit, 2019; CDC, 2022; Ettman et al., 2021; Farmer et al., 2013; Picard et al., 2022; Santamaria-Garcia et al., 2023; Tamang et al., 2014; Thakur et al., 2020).

From this perspective, Majoka and Schimming (2021), Röhr (2021), and Vega et al. (2017) conveyed that SdoH, which also entails the contextual forces and systems that govern people's daily life conditions and related human health dynamics and outcomes, are modifiable risk factors for the development and onset of ADRD. Moreover, SdoH-related adverse effects to human health dynamics and related outcomes are transversal to sociocultural and related socioeconomic settings.

To these effects, Santamaria-Garcia et al. (2023) evaluated the impact of contextually found SdoH and cardiometabolic factors (CMF) on cognition and functionality of aging lower income demographics in Colombia, South America. These researchers found that that a combination of contextually found SdoH and CMF correctly predicted cognition and functionality. However, contextually found SdoH represented stronger predictors of disease outcome. Santamaria-Garcia et al. (2023) findings inform this dissertation on the impact of inequities and inequalities in the development, onset, and prevalence of ADRD, especially among lower income demographics and related economic minorities. Hence, below is the analysis of the scientific literature found relevant to this dissertation on each of SdoH (educational attainment, income, housing, and pollution) and their role in the proposed association with ADRD prevalence.

Educational Attainment

I assumed that the adverse effects of contextually found SdoH (educational attainment, income, housing, and pollution) are cumulative and additive. Where longer and sustained exposures would lead to greater odds of worse health outcomes. To these effects, this study assumes that the reported educational attainment of the population has

been obtained earlier in life: <20 for HS, <25 for college, <35 for graduate, and <40 for any post-graduate degree. This assumption integrates the cumulative influence of contextually found SdoH on educational attainment and the risk for ADRD, prevalence, development, and onset, to which most available literature points to a resilient if not a protective, effect against cognitive decline (Eng, 2022). However, the literature needs to clarify whether the time of highest educational attainment increases or diminishes such attributed protective effect against cognitive decline. Nor is it clear how contextual SdoH influence the educational attainment-cognitive decline association.

Rosselli et al. (2022), using a cross-ethnocultural review, analyzed the differences in neuropsychological test performance, biomarkers, and educational and culture-related variables in ADRD research. These researchers found significant adverse effects on neuropsychological test performance due to low educational attainment and ethnocultural baggage, biases from the research designers, and the underrepresentation of minority ethnocultural groups. Rosselli et al. (2022) inform this dissertation on the reported effects of misdiagnosis, especially in underrepresented demographics with lower educational attainment, often related to lower income demographics and related minorities which could be assessed from the SdoH framework to provide culturally sensitive public health strategy in consensus with the perspectives of researchers and the community being studied. Moreover, Roselli et al. (2022) provide insight into the potential exacerbation of ethnocultural beliefs and practices influencing specific socioeconomic settings and their contextual SdoH.

As conveyed by Volchik et al. (2018) and acknowledged in the SdoH framework

(CDC, 2022), educational attainment in a globalized market economy, especially post-secondary education attainment, promotes human development with economic growth necessary to access better and quality health care services and infrastructure. Indeed, educational attainment in this society determines the opportunities for human development and economic growth of individuals and their dependents and related limitations to their natural and built environments. These opportunity limitations include income, access to health care insurance, infrastructure and services, further education, housing, and income generation related to employment level, status, and opportunities. To these effects, Shrider et al. (2021) informed of the U.S. population's income and poverty as of 2020. These researchers found that in the United States, income and poverty vary by several sociodemographic factors, such as household type (family vs. non-family), race/ethnicity origins, age, nativity (native vs. foreign), geographic area (Northeast, Midwest, South, and West), metropolitan statistical area (MSA) status (inside MSA vs. Outside MSA), and the educational attainment of householders >25 (see Appendices A–C).

Furthermore, Farina et al. (2022) evaluated the association of dementia prevalence decline (2000-2016) related to improvements in educational attainment in the United States. These researchers further related the prevalence declined with the related incidence and mortality due to dementia with the reported educational attainment improvements in the United States. On the other hand, Hayward et al. (2021) also sought to understand the different trends in dementia prevalence across age and race/ethnic groups and the role of educational attainment changes influencing these trends. To these

effects, Farina et al. (2022) and Hayward et al. (2021) pointed out a continuing decline in dementia prevalence related to continuing educational attainment improvements in older and lower income demographics.

Income

Income in this dissertation entails monetary assets necessary to afford the cost of living in society. As such, income, while often derived from work (wages), also includes governmental supplemental subsidies often received in situations that warrant financial vulnerability. One of the most significant debates in society entails the concept of living wages vs. minimum wages. On the other hand, in this globalized and open market economy model, a person's ability to generate and amass income from work decreases with age, often related to physical and cognitive decline. These facts are exacerbated in the lower income demographics and related economic minorities of society and whether they can survive and eventually break away from contextual poverty-disease conundrums. Perhaps the genesis of the endemicity of diseases among and across socioeconomic and cultural spectrums (Arapakis et al., 2021; CDC, 2022; Lock, 2014).

Income is among the most significant variables of the SdoH influencing human health dynamics and related outcomes, where lower income demographics and related economic minorities are disproportionately burdened by disease and related quality of life. To these effects, Arapakis et al. (2021) evaluated the 2016 dementia prevalence variation associated with the socioeconomic status of non-Hispanic whites >70 across the United States and England. These researchers found dementia prevalence was higher among lower income demographics and related economic minorities in non-Hispanic

whites >70 in both countries, with 9.7% overall dementia prevalence in England (95% CI 8.9% to 10.6%) and 11.2% in the United States at 11.2% (95% CI 10.6% to 11.8%), $p < .0055$. To these effects, the 2016 dementia prevalence among the lowest income decile was 18.7% (95% CI 16.6% to 20.8%) in the United States, nearly twice when compared to the U.S. age-adjusted 2016 dementia prevalence of 8.5% (Arapakis et al., 2021; Hudomiet et al., 2022). Moreover, Arapakis et al. (2021) linked the lower income generation to lower educational attainment and low wealth related to housing status, all with embedded potential life-course and cumulative burdens that could influence disease outcomes. To these effects, Shrider et al. (2021) informed of the U.S. population's income and poverty as of 2020. These researchers found that in the United States, income and poverty vary by several sociodemographic factors, such as household type (family vs. non-family), race/ethnicity origins, age, nativity (native vs. foreign), geographic area (Northeast, Midwest, South, and West), metropolitan statistical area (MSA) status (inside MSA vs. Outside MSA), and the educational attainment of householders >25. Moreover, Shrider et al. (2021) indicated that household income, on average, decreased by approximately 3%, with non-family households having an annual average household income of $40,464. That is only 60% of the U.S. average for all households ($67521) and approximately only 47% compared to family households averaging ($6,732) for 2020. Shrider et al. (2021) further elucidated that the elderly, Hispanics, non-Hispanic Blacks, females, non-metropolitan residents, and lower educational attainment demographics continued to be historically and disproportionately burdened by income inequality (see Appendices A–C). Moreover, Yaffe et al. (2021) evaluated military service-related risk

factors in female veterans for developing dementia, finding that military service showed a magnification effect on risk factors observed in civilian women in the United States. Yaffe et al. (2021) pointed out that these effects, occupational hazards coupled with delayed pregnancy due to personal and professional goals based on women's contextual SdoH and ethnocultural beliefs and practices, could represent a magnified risk for the development and onset of ADRD in the veteran female communities often identified among lower income demographics and related economic minorities. Yaffe et al. (2021) inform my research on the socioeconomic and ethnocultural factors that revealed a two-fold risk for ADRD in female veterans over civilian women who already have a two-fold risk for the development and onset of ADRD over civilian males. Furthermore, Yaffe et al. (2021), who coincide with Avdyu & Nayyar (2020), Goldman et al. (2020), and Samuel et al. (2020) further help point out the effects of SdoH regarding income and related occupational hazards exacerbating ADRD outcomes, especially in the U.S. context of chronic diseases, often disproportionately affecting lower income demographics and related economic minorities (Avdyu & Nayyar, 2020; Goldman et al., 2020; Samuel et al., 2020; Yaffe et al., 2021).

Housing

This dissertation ponders housing and housing status in the context of a globalized open market economy and related social and economic stratifications and derived disparities and inequalities that often catalyze and exacerbate the adverse influence of SdoH on human health dynamics and related outcomes, known to affect lower income demographics and related economic minorities disproportionately. From that perspective,

housing status, from access and ownership through infrastructure quality and location to family dynamics related to income inequalities and socioeconomic burdens, represents, alongside education income and environmental pollution, the contextual possibility of a physical, mental, and financial shelter for people to secure human development and related economic growth that would provide access to quality educational and health care services and infrastructure (Balls-Berry & Babulal, 2022; Babulal et al., 2022; Beard et al., 2022; Dawes, 2020; Farmer et al., 2013; Jutkowitz et al., 2022; Shrider et al., 2021; van den Biggelaar 2021; Yaffe et al., 2021).

Babulal et al. (2022), through a systematic review of existing studies, evaluated the association between the aging and increasing homeless population and their increased risk for ADRD in the U.S. context of the COVID-19 pandemic and related SdoH (employment and housing). Babulal et al. (2022) conveyed that the exacerbating effects of SdoH on disease outcomes are contextually modifiable risk factors. These researchers found that approximately 66% of the evaluated literature pertained to homelessness among military veterans, which aligned with Jutkowitz et al. (2022). Moreover, Babulal et al. (2022) pointed out homelessness as part of a complex relationship of risk and consequence of ADRD that is also observed in other psychiatric disorders, substance abuse, and traumatic injuries. Babulal et al. (2022), who coincide with Shrider et al. (2021), van den Biggelaar (2021), Jutkowitz et al. (2022), and Yaffe et al. (2021), inform this dissertation on the conjugation of SdoH (educational attainment, income, and housing) influencing the prevalence, development, and onset of ADRD and often disproportionately affecting lower income demographics and related economic minorities

in the U.S. context of chronic disease (Balls-Berry & Babulal, 2022; Babulal et al., 2022; Shrider et al., 2021; van den Biggelaar 2021; Jutkowitz et al., 2022; Yaffe et al., 2021).

To these effects, Beard et al. (2022), through a scoping review, evaluated the association between protracted or continuous/extended homelessness and the increased risk for development, onset, and prevalence of ADRD. These researchers coincided with Babulal et al. (2022) and Balls-Berry & Babulal (2022) in that protracted homelessness significantly impacts the risk increase for the development, onset, and prevalence of ADRD. Moreover, Beard et al. (2022) pointed to a lapse in research on the association between homelessness and dementia. From the SdoH perspective, these researchers indicated that dementia represents a global public health concern, and up to 40% of all dementia may be attributed to SdoH as potentially modifiable life-course risk factors.

Other housing-related factors affecting cognitive decline and ADRD are assisted living scenarios, nursing homes, age of onset, family dynamics, and related social isolation. To these effects, Beeber et al. (2020), recognizing that >40% of the U.S. assisted living population has dementias, evaluated the association between antipsychotics and other psychotropics prescribed in assisted living scenarios, employing a 250 community sample size from across seven states in the United States. Beeber shed light on the use and potential abuse of antipsychotics and other psychotropics in these scenarios, pointing out that 19% of residents used antipsychotics, and 27% suffer from dementia. 46% of assisted living patients used antidepressants, whereas 24% were on anxiolytics/hypnotics. Moreover, communities that lack an RN or LPN prescribe antipsychotics twice the rate of communities with an RN or LPN (34% vs. 17%; $p<.001$).

This research further points and agrees with Balls-Berry & Babulal (2022) regarding the SdoH-related health disparities of dementia in the United States.

Helvik et al. (2023), through a mixed methods design, evaluated the association between family-caregiver experience and six predefined and related aspects that influence the everyday life of both caregivers and patients with early or young onset dementia (YOD <65). These six aspects included daily activities, social networks, close relationships, behavior, safety, and economy. Helvik et al. (2023) found that family caregivers for YOD patients acknowledge few unmet needs. However, frontotemporal dementia patients' behavioral and close relationships were significantly reported ($p < 0.1$) compared to AD patients. Moreover, approximately 19% of caregivers reported that YOD patients are burdened by disrupted daily activities, unintentional loss of previous social network, losing close relationships but maintaining a friendship with the spouse, and unpredictable behavior that adversely changes their life, health, and posits related life risks, within their households. These conditions further represent a significant economic insecurity risk for present and future life and related care costs. To these effects, Hilman et al. (2023) conveyed that, among caregivers and related dementia patients, uncertainty, the fragility of care structure, and personal independence represent cumulative pressures and concerns often related to SdoH that burden the household and familial health and interpersonal relationships. Jutkowitz et al. (2022) evaluated the association between aging housing-insecure military veterans and the prevalence of ADRD for that demographic group in the United States. Jutkowitz et al. (2022) found that ADRD

prevalence among housing-insecure veterans was 3.66% for homeless veterans, 13.48% among at-risk veterans, and 3.04% for housing-secure veterans.

Moreover, ADRD housing-insecure veterans used more acute care and were likelier to be admitted to nursing homes than veterans with stable housing conditions. At-risk (not homeless) veterans used the Veterans Administration's paid home and community-based care compared to t stable housing veterans. Furthermore, ADRD prevalence, higher among housing insecure veterans (homeless and at-risk) compared to stable-housing housing veterans, informs this dissertation of the importance of housing status and quality of infrastructure evaluated from the SdoH framework. To these effects, Piña-Escudero et al. (2022) evaluated the association between homelessness and neurodegenerative diseases of the brain (NDDB). These researchers found that nearly 50% of the U.S. homeless population is older than 50, pointing out that NDDB may represent a significant factor promoting homelessness in vulnerable older adults burdened by the known adverse effects of contextually found SdoH. These findings reinforce the understanding of the significant role of housing and related access, quality, and infrastructure as contextual SdoH viewed as modifiable risk factors of disease outcome.

Furthermore, van den Biggelaar (2021) evaluated the associations between housing (status and quality) and related socioeconomic indicators for urban and rural settings and five different health outcomes: psychiatric disorders, intellectual disability, dementias, and somatic, mobility-related problems in the Netherlands. These researchers found correlations between inadequate housing quality and higher mental and physical health risk. Moreover, higher levels of urbanization were associated with a higher risk for

dementia development, onset, and prevalence. In contrast, low levels of urbanization correlated with a higher risk for physical health problems. To these effects, van den Biggelaar (2021) pointed out that, after controlling for income, a significant implementation of social housing in a neighborhood correlated with mental and physical health problems. These findings depict the adverse influence of contextual SdoH (educational attainment, income, housing, and pollution) regarding housing access, status, quality of infrastructure, and geographic location as evaluated through the SdoH framework in this dissertation.

Environmental Pollution

Environmental pollution correlates to the ecotoxicity levels of the air, water, light, and noise in the natural and built environment. Environmental pollution exacerbates the development, onset, and prevalence of non-communicable/chronic diseases (i.e., T2DM, AH, asthma, CVD, and ADRD). Environmental pollution, often related to human economic activities, disproportionately affects lower income demographics and related economic minorities and represents a modifiable risk factor for disease outcomes. From this perspective, the SdoH provides the appropriate framework to evaluate the phenomena and related adverse effects governing human health dynamics and their outcomes in a cumulative geo-temporal relationship, which must be addressed contextually to promote a sustainable approach to positive social change with human development and economic growth that supports equality of access to housing, educational and health care infrastructure and services that reduces disparities and inequalities (Anderson et al., 2023; Di Fonzo et al., 2022; Dawes, 2020; Farmer et al.,

2013; Marmot & Bell, 2019; Picard et al., 2022; Power, 2020; Schikowski & Altuğ, 2020; Walker, 2014; Younan et al., 2022).

Picard et al. (2022) evaluated the association of Apolipoprotein B (apoB) and tau pathology in AD. The researchers found that apoB was associated with low-density lipids and dementias. They also found that the increase of apoB/A correlated with increased exposure to volatile organic compounds polluting the environment. Picard et al. (2022) inform my dissertation on the relationships of environmental pollution influences on concurring CVD, T2DM, and ADRD.

Moreover, Schikowski and Altuğ (2020) evaluated the role of air pollution protracted exposure in cognitive impairment and decline in older adults. These researchers found that these associations have been understudied and that even low levels of air pollution correlate to adverse cardiovascular health. Schikowski & Altuğ (2020) inform my dissertation of the imperative need to understand the association between air pollution and cognitive decline and impairment, which is crucial to develop adequate and culturally sensitive public health strategies to mitigate and eliminate these risks, whose cumulative effect is dependent on a geo-temporal relationship to contextual SdoH.

Through a longitudinal cohort study, Younan et al. (2020) evaluated the association between particulate matter with an aerodynamic diameter of <2.5 μm (PM2.5) and the increase in risk for ADRD. Younan et al. (2020) evaluated the early decline of episodic memory related to PM2.5 and increased neuroanatomic risk of ADRD in females (n = 998; aged 73–87) participants of the Women's Health Initiative Study of Cognitive Aging and MRI, including annual episodic memory assessment by the

California Verbal Learning Test between 1999–2010, measuring immediate free recall/new learning and delayed free recall including up to two brain MRI scans. These researchers found that PM2.5 correlated with more significant immediate recall and new learning declines. After adjusting for potential confounders, such decline significantly increased annually by 19.3% with each interquartile increment (2.81 kg/m^3) of PM2.5. Long-term PM2.5 exposure correlated with increased AD pattern similarity scores. Moreover, these associations were observed also in the absence of dementia, stroke, and small-vessel ischaemic disease volumes cases. Thus, these findings indicate that PM2.5 ecotoxicology influences ADRD development, onset, and prevalence. Younan et al. (2020) concluded that protracted PM2.5 exposure promotes early decline of immediate free recall/new learning at the preclinical stage, which, independent of cerebrovascular damage, is mediated by gradual deterioration of grey matter often related to the increased risk for ADRD development, onset, and prevalence. These findings were further supported by Power (2020), who indicated that while the implications of Younan et al. (2020) findings regarding ADRD development, onset, and prevalence are multifactorial, multidimensional, responding to geo-temporal relationships, air pollution exposure as an SdoH is a modifiable risk factor for disease outcome.

Chronic Diseases as Predictor Variables

This section of the literature review is dedicated to evaluating the available literature on T2DM and AH in their roles influencing ADRD prevalence related to contextually found SdoH in the United States.

Type 2 Diabetes Mellitus

Diabetes mellitus is a life-course chronic disease involving a deficient and autoimmune response to either the production or use of insulin in cell metabolism needed to convert foods into glucose to fuel the energy needed to carry out essential life functions and work (CDC, 2023a). Among the three basic types of recognized diabetes mellitus is type 1 diabetes mellitus, often genetically or congenitally related and comprises 5%-10% of cases in the United States. Gestational diabetes refers to diabetes mellitus acquired during pregnancy in women who do not already have diabetes. Gestational diabetes affects 2% to 10% of pregnancies yearly in the United States. Lack of management of gestational diabetes is often related to congenital diseases affecting the newborn. T2DM, on the other hand, is often related to lifestyles, autoimmune, and environmental factors, with over 37 million cases comprising 90-95% of cases in the United States. Moreover, the not yet well-understood pathogenesis of T2DM has led to the inclusion of MetS, latent autoimmune diabetes in adults, and insulin resistance, all related to concurring comorbidities such as CVD, rheumatoid arthritis (RA), AH, ADRD and even hormonal dysregulation due to pre-menopause, menopause, and postmenopause physiological changes, and latent autoimmune diabetes in adults all involving subjacent pathophysiological mechanism of low-chronic inflammation, where besides genetic load, contextual SdoH propitiate and exacerbate the effects of these diseases. Among these contextual SdoH are educational attainment, income, housing, and environmental pollution (Wang, 2020; Scheyer et al., 2018). Thus it is imperative to understand better how these T2DM and its encompassing group of related diseases influence the

prevalence, development, and onset of ADRD (Jones et al. 2021; Buzzetti et al. 2020; Wang, 2020; Carlsson, 2019; Cousminer et al. 2018; Mishra et al. 2018; Pozzilli & & Pieralice, 2018; Scheyer et al. 2018; Banerjee & Bytyci, 2016).

T2DM, a leading cause of death in U.S. adults>18, is a significant incapacitating disease that disproportionately imposes health and economic burdens on patients, families, and society, especially among lower income demographics and related economic minorities, where older subjects bear most of the adverse outcomes. These phenomena further concatenate health and economic burdens impacting the individual through the societal level, which needs to invest more in the research, care, and treatment of the disease and related socioeconomic limitations that these diseases impose. From this perspective, T2DM seems entangled in a potential disease poverty conundrum in the context of related chronic comorbidities (i.e., CVD, AH, and ADRD), food insecurity (FI), and related FEI become modifiable SdoH and risk factors that could transcend generations of Americans.

To these effects, and in the realm of this dissertation, Bianco (2016) evaluated the prevalence of T2DM in the U.S. Latino community, finding a correlation between T2DM-related micro-bleeding in the brain tissue. This cerebrovascular disease has symptoms and pathophysiological mechanisms similar to ADRD, indicating the need to understand the relationship between T2DM and ADRD. Bianco (2016) informs this dissertation on evaluating T2DM and related CVD comorbidities from the contextual SdoH and ethnocultural influencing ADRD prevalence, development, and onset. To these effects, Picard et al. (2022) and Schikowski & Altuğ (2020) converged to point to the

geo-temporal varying and exacerbating effects of pollution-related SdoH on ADRD and concurring chronic comorbidities (i.e., T2DM, AH, RA, and CVD),

Groeneveld et al. (2018) evaluated mild cognitive impairment (MCI) in T2DM patients related to grey matter atrophy rather than a vascular pathology. These researchers found that T2DM patients with MCI showed a brain volume reduction in the temporal lobe and grey brain matter in the subcortical lobe. This finding points to the relationship between T2DM and dementia-causing diseases. Groeneveld et al. (2018) further inform my dissertation in that the imaging-correlates findings could suggest a pathophysiological mechanism linking T2DM and ADRD, pointing out that MCI patients showed significantly lower educational attainment than non-MCI. At the same time, low educational attainment is often related to the disproportionate effects of SdoH, known to vary geo-temporally affecting human health dynamics and related outcomes. It also indicates the need for ethnocultural representation in ADRD research and public health interventions. Groveland et al. (2018) further provide scientific support to the possible link of T2DM and related CVD comorbidities in a socioeconomic and geo-temporal context, which, viewed from the income-stratified U.S. market economic model, defines access to quality health care infrastructure and services.

Mielke (2018) evaluated the difference in the development and onset of AD based on gender. This researcher pointed out that gender disparities in the prevalence, development, and onset of ADRD in women, who disproportionately bear the incidence burden with a two-fold risk over men in the United States, are related to women's longevity. Mielke informed this dissertation by offering a contrasting argument compared

to the scientific belief that ADRD is not determined by age but that cognitive declines are related to disease-causing neurodegeneration of brain tissue. Chief among these diseases, are physiological and psychological changes that women experience throughout their lives, especially around the age of menopause, and with similar pathophysiologic mechanisms of low-chronic inflammation as observed in T2DM and related CVD comorbidities, rheumatoid arthritis, and menopause physiological changes.

Picard et al. (2022) evaluated the association of apoB and tau pathology in AD. apoB is associated with low-density lipids and dementias. These researchers found that the increase of apoB to increased exposure to volatile organic compounds polluting the environment. Picard et al. contribute to my dissertation as it correlates CVD, T2DM, and dementia to environmental pollution. To these effects, a high ratio of apoB/apoA-I points to CDV and early tau dysregulation in asymptomatic subjects, pointing to a high risk or predisposition to developing visuospatial cognitive decline related to ADRD (Kaneva et al., 2015; Picard et al., 2022; Tamang et al., 2014). Thus, ApoB and the apoB/apoA-I ratio, which would vary geo-temporally, could prove early predictors of ADRD in the U.S. context of chronic disease and pollution-related SdoH.

Poznyak et al. (2020) evaluated underlying pathophysiological mechanisms relating to ADRD, T2DM, and CVD. These researchers found that low-chronic inflammation processes observed across clinical manifestations of several different diseases such as menopause, T2DM, related CVD comorbidities, rheumatoid arthritis, and arteriosclerosis that leads to cardiovascular-related mortality are linked to the neurodegenerative processes observed in dementia cases. Poznyak et al. (2020), who

coincide with Savolainen-Peltonen et al. (2019) and Scheyer et al. (2020), further inform the scientific background of this dissertation, tying the ADRD, T2DM, related CVD comorbidities, and menopausal physiological and psychological changes, all related to low-chronic inflammation and specific to women and whose effects vary geo-temporally.

To these effects, Savolainen-Peltonen et al. (2019) evaluated the association between postmenopausal hormonal therapy and ADRD development and onset. These researchers found that women younger than 60 who undergo a long-term (>10 years) therapeutical use of estrogen-progestogen or vaginal estradiol hormonal treatment are at an increased risk for developing AD. Moreover, this increased risk for AD was not influenced by the age of hormonal therapy initiation. Savolainen-Peltonen et al. (2019) inform my dissertation on the socioeconomic and ethnocultural processes related to hormonal therapy uptake and timing related to the development and onset of ADRD. Learning of the time before clinical manifestations of ADRD provides a plausible window of public health intervention for women in the upper age brackets. Scheyer et al. (2020), who evaluated women's risk for ADRD related to menopausal changes and treatment, found that the female gender represents a significant risk factor in AD development and late onset. Scheyer et al. (2020) also inform this dissertation as it supports the idea that ADRD-related pathology often begins a decade or more before their clinical manifestations, and the contextual life course effects of SdoH influence it (Scheyer et al., 2020; Wang et al., 2020).

Rodríguez and Campbell (2017) evaluate racial/ethnic disparities in T2DM disease burden. These researchers found that in the United States, African Americans

(13.2%) and Hispanics/Latinos (12.8), often recognized among lower income demographics and related economic minorities, have approximately a two-fold prevalence of T2DM than non-Hispanic Whites. Moreover, there is a significant prevalence variation (6% to 24%) of T2DM among Native Americans from Alaska through Southern Arizona. There is also a significant variation of prevalence among Hispanics/Latinos, where Puerto Ricans have a 14.8%, Mexican Americans at 13.9%, Cubans at 9.3%, and Central and South Americans combined have an 8.5% prevalence. Rodriguez and Campbell (2017) inform this dissertation and coincide with Bianco (2016) in evaluating T2DM and related CVD comorbidities and the contextual socioeconomics and ethnocultural influences on the development and onset of ADRD. It also informs the research from the influential aspects of SdoH, known factors to govern human health dynamics and related outcomes.

Vera et al. (2019) evaluated the association between MetS, the immune system, and arthritic disease. These researchers found that a conglomerate of metabolic and cardiovascular physiological problems and derived health outcomes known as MetS are intertwined and often competing T2DM-related comorbidities and derived vascular and cardiovascular diseases, including insulin resistance, dyslipidemia, hypertension, obesity, and abdominal adiposity. Vera et al. (2019) further insights that there seems to be an underlying pathophysiological mechanism related to the dysregulation of pro-inflammatory adipokines secretion, observed in all these diseases, and low-grade chronic inflammation prevalent in patients with obesity, MetS, rheumatoid arthritis, CVD, T2DM, and ADRD, all observed to vary geo-temporally. Vera et al. (2019) further

inform this dissertation on the ethnocultural beliefs and practices that often exacerbate SdoH affecting human health and related outcomes, including care and knowledge of these factors potentially influencing the development and onset of ADRD often disproportionately affecting lower income demographics and related economic minorities.

Wang et al. (2021), through a community-based cross-sectional study and linear regression (LR) analysis grounded on the HBM and the SEM of health promotion, analyzed the extent to which MetS could be associated with the risk of cognitive impairment in the people of Jidong, a Chinese community in China. Their study recruited 5854 participants with an approximately even number of males and females. Participants were of 44 years +/-14 SD years old. The researchers assessed participants for cognitive function and MetS via the Mini-Mental State of Examination Scale and the International Diabetes Federation criteria. These researchers found that MetS is associated with cognitive impairment.

Moreover, visceral adiposity and AH correlated to an increased risk for cognitive impairment, a clinical aspect of dementia. Wang et al. (2021) related their study to similar previous research on a Latino community in California, the experimental work on MetS in laboratory rats with high fructose intake, and the disruption of insulin brain signaling. Wang et al. (2021) inform this dissertation regarding MetS and similar conditions, like T2DM and concurring AH related to ADRD. This approach lends similar methodologies to analyze whether contextually found ethnocultural beliefs and practices, SDoH inequalities (i.e., education attainment, income, housing, and pollution), and its

political precursors correlate or are associated with an increased risk for ADRD in women and lower income demographics and related economic minorities. To these effects, Wang et al. (2021) community-based cross-sectional study also sheds light on the replicability of the methodology adjusting for demographic characteristics and contextually found ethnocultural beliefs and practices known to exacerbate SDoH and related political precursors.

Hypertension

AH is the clinical condition of living with high blood pressure. AH is the measuring of blood pressure created by arterial blood flow from (systolic) and into (diastolic) the heart. Blood pressure naturally fluctuates during the day, and it is measured in millimeters of mercury (mmHg). To these effects, the systolic/diastolic or output/input pressure ratio gives a sense of the heart's mechanical pumping efficiency. Normal blood pressure ranges are 120/80 mmHg regardless of age (CDC, 2021). Hypertension is medically diagnosed and confirmed through repeated measurement yielding 140/90 mmHg or higher, including diabetes mellitus or renal failure patients. This CDV is treatable via diet, exercise, and antihypertensive pharmacological drugs. Hypertension is among the leading causes of death in U.S. adults >18. It is also known to cause end-organ damage (i.e., heart, brain, kidneys, and eyes), stroke, ischemic heart disease, and ADRD, especially when concurring with chronic diseases (i.e., T2DM and related CVD), ethnocultural and SdoH (Aggarwal et al., 2021; CDC, 2021; Jordan et al., 2018).

To these effects, Aggarwal et al. (2021) evaluated the 2013-2018 AH prevalence, awareness, treatment, and control in U.S. adults ≥18 stratified by race/ethnicity. These researchers found that, on average, 48.6% of U.S. adults ≥18 have controlled hypertension (blood pressure ≥ 140/90 mmHg). However, age-adjusted blood pressure control rates reveal racial/ethnic disparities often related to contextually found SdoH, which is known to affect lower income demographics and related minorities disproportionately.

Furthermore, Aggarwal et al. (2021) reported that blood pressure control rate for non-Hispanic Asians was 37.8%, and an adjusted odds ratio (aOR) of 0.68 [95% CI, 0.55–0.84], p< .001; for non-Hispanic Blacks was 39.2%, with an adjusted odds ratio (aOR) of 0.71, and for Hispanic 40.0%, with an aOR of 0.71 [95% CI, 0.58–0.88], p< .003, compared to non-Hispanic Whites at 49.0% [46.8%–51.2%]. Furthermore, AH prevalence adjusted for 2018 in the United States revealed that non-Hispanic Black adults had a 45.3% AH prevalence with an aOR of 2.24 [95% CI, 1.97–2.56], p< .001, non-Hispanic Asians 31.8%, aOR=1.00, Hispanics 31.6%, aOR=0.98, and other racial/ethnic groups 36.6%, aOR=1.33 compared to non-Hispanic White adults at 31.4% AH prevalence, All racial/ethnic groups had with similar awareness and treatment rates (Aggarwal et al., 2021).

However, Aggarwal et al. (2021) also reported that T2DM prevalence among the same racial/ethnic groups was 26.9% for Hispanics, 26.2% for non-Hispanic Asians, 24.3% for non-Hispanic Blacks, and 27.4% for all other racial/ethnic groups compared to 21.6% T2DM prevalence in non-Hispanic Whites. 19.4% of Hispanic adults were

uninsured, 13.2% of non-Hispanic Blacks, 8.1% of non-Hispanic Asians, and 8.8% of all other ethnicities compared to 6.3% of non-Hispanic Whites uninsured adults. These findings point to ethnic/racial disparities of disease burden, awareness, and treatment for AH and T2DM related to contextual SdoH. Aggarwal et al. (2021) inform this dissertation of the adverse effects of contextual SdoH influencing AH and T2DM among ethnocultural groups and the disproportion disease burden known to affect lower income demographics and related economic minorities in the United States.

Mishra et al. (2020) evaluated the association between cognitive decline, a known clinical sign of dementia, and AH. These researchers found AH to be a significant risk factor for the development, onset, and prevalence of VD. Hence, AH's protracted management with antihypertensive medications for optimal blood pressure could effectively delay and possibly prevent cardiovascular complications (i.e., stroke and kidney failure) and related ADRD effects. Moreover, Mishra et al. (2020) found no significant difference in the benefits attributed to any specific antihypertensive medications class to prevent cognitive impairment.

Regarding the association between MD and AH, Mogi (2019) evaluated the association between AH and MD among elderly adults in South Korea. MD entails AD and VD. To which AH and related blood vessel disorders are among the most significant risk factors. Mogi (2019) reported that the cumulative burden of AH from Mid-life onward correlated to the incidence of dementia. Moreover, antihypertensive pharmacological treatment in elderly patients does not prevent the development and onset of dementia. To these effects, the renin-angiotensin system (RAS) is intrinsically

involved in hypertension and related life course cumulative diseases and may represent a subjacent pathological mechanism in dementia; thus, RAS regulation can be acquired to modifiable lifestyle risk factor accounted for in contextual SdoH to potentially delay or prevent dementia. Mogi (2019) informs this dissertation from the scientific pathologic perspective entangled with the life course effects often attributed to contextually found SdoH, in which blood pressure control from earlier ages may prove an effective measure against ADRD development, onset, and prevalence.

Xianglin et al. (2023) evaluated the association between the risk of ADRD and the types of antihypertensive medications in colorectal cancer survival patients. These researchers found that among colorectal cancer patients with hypertension, ADRD risk was higher in hypertensive patients receiving angiotensin II–inhibiting antihypertensive drugs than those receiving angiotensin II–stimulating antihypertensive drugs. Moreover, the risk increased with age and was higher among Hispanics and non-Hispanic Blacks regarding AD, VD, dementia with Lewy bodies, MCI, and other dementias. In contrast, a higher risk for frontotemporal degeneration and dementia was observed in the non-Hispanic all other ethnic groups compared to non-Hispanic Whites. Xianglin et al. (2023) pointed out clinical hypertension treatments in concurring comorbidities and their related risk disparities for developing ADRD across the racial/ethnic and sociodemographic spectrums. Xianglin et al. (2023) inform this dissertation on the risk for ADRD on concurrent comorbidities and treatments from the clinical and SdoH perspectives.

Type 2 Diabetes Mellitus–Arterial Hypertension Context

There is a large body of scientific literature that links T2DM, AH, SZ, and OP, all

chronic diseases directly and indirectly related to ADRD development, onset, and prevalence. T2DM and related treatment promote bone mineral density loss (OP; Ferrari et al., 2020; Jackulliak et al., 2019; Hagi et al., 2021; Holt, 2019; Moshin et al., 2019; Poiana & Capatina, 2017; Rehling et al.,2019; Sheu et al., 2022; Yuhao et al., 2019), a risk which increases in postmenopausal diabetic women (Roomi et al., 2019).

T2DM and related treatment may impact SZ, and SZ treatment increases T2DM incidence (Guerrero Fernández de Alba et al., 2020; Haggi et al., 2021; Holt, 2019). On the other hand, MetS, T2DM, and AH significantly correlate with global cognitive impairment in SZ patients (Hagi et al., 2021). To these effects, Postolache et al. (2019) posited that SZ and major depressive disorder in untreated patients correlated with a higher risk for T2DM and MetS. Moreover, SZ, major depressive disorder, T2D, and MetS are often concurrent comorbidities that increase CVD risk. The concurrence of these comorbidities may configure a health-poverty conundrum that needs to be understood better to treat and prevent both the chronic comorbidities and the related ADRD outcome. Therefore, this dissertation includes SZ and OP in the T2DM-AH context of the United States to evaluate the association between SdoH and ADRD prevalence in the U.S. context of T2DM and AH.

Schizophrenia

SZ entails a mental disorder often characterized by psychotic episodes that impact motor and cognitive abilities, reality perceptions, and emotional and social responsiveness. Although a treatable condition, SZ's impact on cognitive abilities is often diagnosed from an early age (typically from late adolescence). SZ is a protracted

condition and can be severe and disabling. While SZ is not a form of dementia, SZ patients have an elevated risk of developing AD. SZ and AD have been correlated by their similarities in white matter anomalies and cognitive shortfalls as characteristics of these diseases. In the United States, SZ prevalence ranges between 0.25% and 0.64% (de Oliveira-Souza et al., 2007; Kochunov et al., 2021; National Institute of Mental Health, n.d.). To these effects, de Oliveira-Souza et al. (2007) evaluated the association between SZ and dementia. These researchers found that SZ may lead to dementia as a final consequence of SZ progression and as a pharmacologically responsive reversible state. Both mechanisms require further investigation. Kochunov et al. (2021) evaluated the association between SZ and AD in aging SZ patients based on the similarity of the cerebral white matter deficit development also observed in AD patients. These researchers found that a higher regional vulnerability index for AD patients was significantly correlated with cognitive measures in SZ and AD patients. Kochunov et al. (2021) pointed out that these similarities in white matter anomalies could render a new early detection and treatment mechanism common to both diseases. De Oliveira-Souza et al. (2007) and Kochunov et al. (2021) inform this dissertation of the impact of SZ in ADRD and that SZ prevalence could be an early predictor of ADRD.

Osteoporosis

OP is a medical condition characterized by bone density and microarchitecture degradation, thus making the bone less dense, weak, and brittle with a higher propensity to fracture. OP has been correlated to CVD, AH, and ADRD due to the calcification of vessels often promoting VD (Başgöz et al., 2022; Lary et al., 2021; Polyzos et al., 2021;

Zhang et al., 2022). To these effects, Başgöz et al. (2022) evaluate the association between bone mineral density and OP in older adults with and without dementia. These researchers found that ADRD elder patients showed lower bone mineral density and higher incidence of OP regardless of gender, often located in the hips rather than the lumbar spine. Başgöz et al. (2022) further pointed out that OP in the hip may be associated with the development of ADRD, namely AD and VD. Lary et al. (2021) converged with Başgöz et al. (2022) findings, further adding that OP possesses a greater risk of mortality in AD patients due not only to aging but also physical activity, vitamin D deficiency, sarcopenia, and AD pharmacological treatments. Zhang et al., 2022, also agree with Lary et al. (2021) converged with Başgöz et al. (2022) findings after evaluating the association between OP and the risk or incidence of dementia in Hong Kong. Zhang et al. (2022) found that higher bone mineral density T-scores at the lumbar spine, trochanter, and total hip were significantly associated with a higher risk of dementia in females than males, even after controlling for serum estradiol.

Furthermore, Polyzos et al. (2021), through a systematic review, evaluated the associations between OP and other metabolic diseases, including obesity, T2DM, nonalcoholic fatty liver disease (NAFLD), dyslipidemia, and CVD in postmenopausal women. These researchers found that OP usually coexists with metabolic diseases, including obesity, T2DM, NAFLD, dyslipidemia, and CVD, in the aging population. Moreover, The OP and metabolic diseases association may surpass that of the concurrent comorbidities prevalence, for which more investigation is needed. These researchers also pointed out that anti-osteoporotic medications may adversely impact the pathogenesis of

metabolic diseases; thus, OP pharmacological concurrent metabolic diseases on a patient-by-patient basis. Başgöz et al. (2022), Lary et al. (2021), Polyzos et al. (2021), and Zhang et al., 2022, converged to inform this dissertation of the impact of OP, and related treatments in the development, onset, and prevalence of ADRD. Moreover, OP prevalence could render an early predictor of ADRD.

Statistical Geospatial Analysis

This literature review section focuses on using GWR and MGWR as statistical evaluation models of spatially varying relationships (SdoH and chronic diseases). While no studies were found related to ADRD prevalence, development, and onset, a few studies were relevant to this dissertation as they focused on the association between SdoH and infection rates and chronic diseases evaluated through GWR and MGWR techniques.

Geographically Weighted Regression

GWR is a local spatial statistical technique based on the MLR model fitted by the OLS model. GWR is used to analyze spatial and temporally varying relationships (i.e., SdoH, disease outcomes, and temperature). In GWR, these spatially variable relationships are assumed to vary at a constant rate with respect to the distance from a specific reference point of measurement. GWR also assumes that the strength of association between the observed spatially varying relationships decreases as the distance between observation points increases (Brunsdon et al., 1998; Charlton et al., 2009; de Bellefon & Floch, 2018; Fotheringham et al., 2003).

Multiscale Geographically Weighted Regression

MGWR is a refinement of the original GWR technique. MGWR allows for incorporating spatially overlapping relationships where the coefficients of the predictor variables (estimated parameters) vary across space at a non-constant rate of change. In MGWR, spatially varying relationships are not assumed to vary at a constant rate with respect to the distance from a specific reference point of measurement. Thus, each predictor variable may operate at a different spatial scale. MGWR also assumes that the strength of association between the observed spatially varying relationships decreases as the distance between observation points increases. The most significant benefit of the MGWR refinement lies in the reduction of statistical standard error and increased statistical power (Boakye et al., 2022; Bonzani et al., 2023; Fotheringham et al., 2017; Iyanda et al., 2020; Oshan et al., 2020; Raymundo et al., 2021; Rzasa & Ciski, 2022).

From the perspective that SdoH are spatial-temporal varying relationships, Boakye et al. (2022) evaluated the association between cancer and non-cancer risk estimates and on-road sources of harmful air pollutants at the census tract level and sociodemographic variables from the U.S. Census Bureau to examine their non-stationary geospatial relationship. These researchers used aspatial and spatial regression models fitted by global OLS, spatial error model, GWR, and MGWR to compare the geospatial distribution of the evaluated relationships. Boakye et al. (2022) found that contrary to the seeming clustering of cancer and non-cancer risks in major urban areas, GWR 7 MGWR analyses revealed that cancer and non-cancer risk correlated with census tracts largely populated by lower income demographics and related economic minorities, among which

Black, Indigenous, and People of Color are found. These findings inform this dissertation on the feasibility and power of GWR and MGWR statistical regression models to evaluate SdoH.

Bonzani et al. (2023) used GWR statistical analysis to evaluate the geo-temporal varying effects of SdoH on COVID-19 incidence and mortality in the United States. These researchers shed light on the importance of understanding the geo-temporally varying effects of the SdoH on disease outcomes and related burdens. These research findings and geospatial methodology inform this dissertation's theoretical framework, design, and associated statistical evaluation of the association between the prevalence of ADRD and SdoH in the U.S. context of chronic disease at the county population level (unit of analysis).

Iyanda et al. (2020), Raymundo et al. (2021), and Rzasa & Ciski (2022) evaluate the associations between SdoH and the spread of the COVID-19 pandemic globally, in Brazil and the United States, respectively. To these effects, Ivanda et al. (2020) found that the proportion of the population aged 15-64 and out-of-pocket expenditure significantly and positively correlated with the global variation in the COVID-19 global outbreak (175 countries). Meanwhile, the population percentage of people that smoke was inversely correlated with COVID-19 at the global level. Raymundo et al. (2021) found that in Brazil, at the municipality level of measurement, a higher GINI coefficient correlated to a higher COVID-19 incidence. Moreover, a higher nurse per 1,000 inhabitants ratio correlated to higher COVID-19 incidence, and the proportional mortality ratio was inversely associated with COVID-19. The Gini index (0 – 100) (World Bank,

2023) though often used as (0-1) scale (OECD, 2023) to express it in terms of percentages, measures income distribution and economic inequality. Throughout this dissertation the (0-1) index scale will be used. A Gini index of 0 epitomizes perfect equality and an index of 1 to the most significant economic disparities. (OECD, 2023; World Bank, 2023). Rzasa and Ciski (2022) found that the SdoH best explained the incidence of COVID-19. To these effects, the social factors showed a medium correlation strength compared to a low correlation of environmental factors regarding COVID-19 incidence. Population density and intensity of human economic activities significantly impacted the incidence and spread of the COVID-19 pandemic.

Furthermore, areas of socioeconomic distress revealed that poverty made the people in these areas highly vulnerable to the COVID-19 pandemic and its known devastating impacts. All three studies by Iyanda et al. (2020), Raymundo et al. (2021), and Rzasa & Ciski (2022) inform this dissertation on the feasibility of employing GWR & MGWR to evaluate ADRD prevalence influenced by SdoH in the U.S. context of chronic diseases. These studies also point to the enhanced statistical power of the GWR and MGWR models compared to the multinomial linear regression approach.

Oshan et al. (2020) evaluate the association between the SdoH impacting obesity in the Phoenix, AZ metropolitan area. Using GWR and MGWR techniques, these researchers found that MGWR yields a lower AIC and AICc value, which reduces standard error, improves statistical power, and renders better results against multicollinearity than GWR. Thus, MGWR helps better understand the SdoH that influences obesity rates by delivering determinant-specific spatial context. Moreover,

Oshan et al. (2020) pointed out that a combination of global and local factors can best model obesity rates, where MGWR readers a more significant yet statistically parsimonious quantitative representation of obesity's SdoH compared to GWR and LR fitted through OLS. These researchers help corroborate the improvement of the statistical power in the analysis of the outcome-predictor association.

Summary and Conclusions

ADRD has had a continuous and sustained increase in prevalence globally and in the United States over the past 4 decades. ADRD entail a conglomerate of neurodegenerative diseases (AD, dementia with Lewy bodies, VD, MD, and MCI that develop into dementia, often clinically signaled by memory and cognitive ability loss. Dementia is not part of a normal aging process. Addressing these issues is needed primarily due to the neurodegenerative nature of ADRD, which disproportionately incapacitates health and financial burdens on the patient, family, caregivers, and society, especially in chronic disease, lower income demographics, and related economic minorities. Regarding evaluating the association between SDoH (education attainment, income, housing, and pollution) and ADRD prevalence in the U.S. context of T2DM and AH, T2DM often impacts the development, onset, and prevalence of ADRD through lifelong complications of the disease exacerbated by contextual SDoH. AH often escorts related CVD and T2DM and impacts the development and onset of ADRD.

ADRD prevalence intertwines with SDoH in a spatiotemporal varying yet modifiable relationship, which, if unattended, could become the genesis of a disease-poverty conundrum affecting current and future generations of Americans. To these

effects, the cumulative adverse effects of lifelong contextually found SDoH disproportionately affect lower income demographics and related economic minorities in the development, onset, and prevalence of ADRD, especially in the U.S. context of chronic diseases like T2DM, AH, and associated CVD. In the United States, civilian females bear a two-fold risk of developing ADRD than males, based only on gender differences and the psychological and physiological changes women experience throughout their lives from menarche through menopause. Moreover, military female veterans have a two-fold risk than civilian women.

SDoH vary geospatially and throughout the social, demographic, economic, and ethnocultural spectrums. SDoH govern human health dynamics and related outcomes, disproportionately affecting lower income demographics and economic minorities. Moreover, SDoH imposes contextual health and financial burdens observed from the individual through the societal level. However, SDoH are modifiable risk factors for disease outcome, upon which intervention could render culturally sensitive and contextually drive public health strategies that catalyze a sustainable approach to human development with economic growth that would promote equal access to quality education, housing, and health care infrastructure and services aiming to reducing and eliminating the observed related inequities and inequalities. Contextually found SDoH render stronger predictors of disease outcome. Hence, these will be used in this dissertation to evaluate the association between ADRD prevalence and SDoH in the U.S. context of chronic diseases (T2DM and AH).

To these effects, it is crucial to understand better the potential associations between ADRD prevalence, SDoH, and chronic diseases for the latter two may render early predicting mechanisms that would elicit culturally sensitive public health measures that catalyze sustainable positive social change through human development with economic growth empowering communities through women, the pillar of the family, the unit cell of society. To these effects, this dissertation portrays SDoH as modifiable risk factors for disease outcomes. As such, it might elucidate new pathways for early intervention mechanisms to mitigate and possibly eliminate SDoH effects governing human health dynamics and related outcomes, especially on lower income demographics and related economic minorities. Moreover, it is worth mentioning that while the existing literature points to higher educational attainment as correlated with reduced risk for ADRD, the literature does not specify whether such seemingly protective factor varies with the age of the highest educational attainment nor concerning the life-course influence of the contextual SDoH impacting the achievement of the analyzed educational attainment and associated reduced risk for ADRD. Hence, this dissertation assumes that the earlier the highest educational attainment is achieved in age, the greater the protective effect against ADRD. This assumption further integrated the perspective of contextual SDoH in an open market economy, where educational attainment significantly reduces the impact of other SDoH (i.e., income, housing, and pollution), rendering better access to quality health care infrastructure and services.

Hence, this study evaluates the association between ADRD prevalence and SDoH (namely educational attainment, income, housing, and pollution) in the U.S. context of

T2DM and AH, two of the often ADRD-related comorbidities and leading causes of death in the United States. Chapter 3 will focus on the methodology and procedures employed for this study evaluating ADRD prevalence (dependent variable) influenced by the independent variables (educational attainment, income, housing, and pollution) in the U.S. context of T2DM (moderator variable) and AH (covariate) controlling for age. Moreover, chapter 3 will also focus on the research design, rationale, data analysis plan, and potential threats to validity to safeguard the reliability of the associated analysis.

Chapter 3: Research Method

Introduction

In this quantitative cross-sectional study, I evaluated the association between ADRD prevalence (dependent variable) and SDoH (namely, educational attainment, income, housing, and pollution) in the U.S. context of T2DM and AH (as predictor variables). Chapter 3 includes sections on the research design and rationale, methodology, data analysis plan, and threats to validity. In the Research Design and Rationale section, I outline which variables and type of research design were most suitable to evaluate the posited RQs and hypotheses. The Methodology section includes details on the target population from the combined 2018 CHR&R and CMS data sets and their related data collection methods. In the Data Analysis Plan section, I discuss my use of the ASU MGWR 2.2 software (ASU, n.d.) for GWR and MGWR statistical analysis and SPSS Version 28 for the corresponding MLR model, as well and all associated data manipulation and statistical tests for this study. The Threats to Validity discussion includes discussion of validity issues and ethical considerations for the study. The chapter ends with a summary of key points and a transition to Chapter 4.

Research Design and Rationale

Using SDoH as the theoretical framework, I examined (a) ADRD prevalence as the outcome or dependent variable and (b) SDoH (educational attainment, income, housing, and pollution) in the U.S. context of T2DM and AH as the predictor or independent variables. The variables, HS graduation rate and adults 25–44 with some postsecondary education, relate to educational attainment. Household median family

Income and 20th percentile population percentage of income, percentage of the population with severe housing problems, and the county's average daily density of fine particulate matter in micrograms per cubic meter (PM2.5) are variables related to for environmental air pollution. I used a quantitative cross-sectional design to evaluate the association between the study variables. I developed the study's RQs and related hypotheses based on the literature on SDoH (Assari, 2018; Bhunia & Shit, 2019; CDC, 2022; Ettman et al., 2021; Farmer et al., 2013; Picard et al., 2022; Tamang et al., 2014; Thakur et al., 2020).

Regarding the data analyses for the study, I did not foresee any time or resource constraints consistent with the design. I used combined curated secondary data sets that encompassed 2018 CHR&R (CHR&R, 2023) and multiple chronic diseases data (CMS, 2018), which I geospatially joined and coded by county using Federal Information Processing System (FIPS) codes for states and counties (National Institute of Standards and Technology, 2023). I statistically evaluated that data using spatial analysis software (i.e., ArcGIS Online and ArcGIS Pro 3.2). I performed MLR, GWR, and MGWR using MGWR 2.2 from ASU's SPARC and SPSS Version 29 were used to examine the associations, if any, between ADRD prevalence and SDoH (educational attainment, income, housing, and pollution) in the United States in the context of T2DM and AH. I sought to identify whether any meaningful and statistically significant associations existed between the prevalence of ADRD and SDoH, T2DM, and AH in the United States (95% CI, $p < .05$).

I used a quantitative cross-sectional design because exposures and related outcomes were measured simultaneously and all variables represented population-level measurements at the county level, which was the unit of analysis (see Burkholder et al., 2019; Cataldo et al., 2019; Frankfort-Nachmias et al., 2019; Lau, 2017; Setia, 2016). This approach helped to elucidate the potential associations between ADRD prevalence, development, and onset regarding the adverse cumulative influences of contextually found SDoH in the U.S. context of T2DM and AH. Knowledge in the epidemiology field could be enhanced by use of this approach. Learning the suspected associations and regression models could render SDoH as early predictors and even spatiotemporal-related predictors.

Methodology

Population

The target population evaluated in this study was the 2018 U.S. population. I analyzed a nationally representative sample from 2018 from the CHR&R (2023) and CMS (2023), with the focus of the latter on multiple chronic disease. The targeted population, data sets, and nationally representative sample size were chosen because (a) ADRD prevalence in the United States quadrupled during the last 4 decades and (b) ADRD traverses socioeconomic and ethnocultural settings, disproportionately affecting lower income demographics and related minorities, especially in the U.S. context of T2DM and AH (CDC, 2020, 2022). To examine potential effects, I used a cross sectional research design rooted in the SDoH framework (Burkholder et al., 2019; Cataldo et al., 2019; Frankfort-Nachmias et al., 2019; Lau, 2017; Setia, 2016).

Sampling and Sampling Procedures

This study employs nationally representative samples of curated secondary data combining the following two for this research effort: The 2018 U.S. CHR&R from the CHR&R and the 2018 U.S. Chronic Diseases data set from the CMS. A nationally representative sample is required since this dissertation uses a cross-sectional design rooted in the SDoH framework evaluating ADRD prevalence at the county population level influenced by contextual SDoH, T2DM, and AH. Having chosen GWR, MGWR and MLR regression models for statistical analysis, an a priori statistical power of at least $\beta = 80\%$ and a statistically significant threshold $\alpha = 0.05$ have been set to determine the minimum required sample size (Cohen, 2013; Cvetković Vega et al., 2021; Haijan-Tilaki, 2011; Lu et al., 2013). Using G*Statistics Software, the minimum sample size was calculated to be 172 counties for a minimum effect size $f^2 = 0.1$ using 10 predictors (see Figure 3). The nationally representative data sample available from HCR&R and CMS contains data for 3,142 counties, which should increase the statistical power (see Figure 4).

Figure 3

A Priori Power F-Critical calculation.

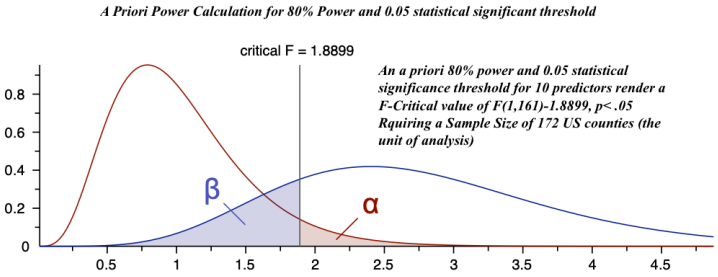
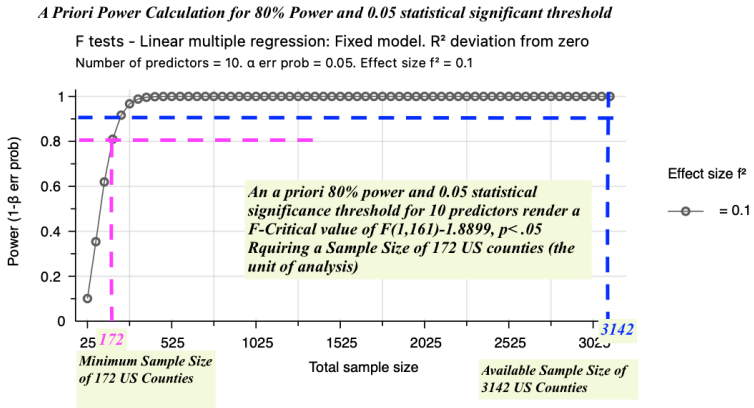


Figure 4

A Priori Power (80%) Used to Calculate the Minimum Sample Size (172 Counties).



The aim of the CHR&R program is to provide data, evidence, guidance, and examples to generate awareness and empowerment of communities to promote health equity and to provide information about the multiple factors affecting health outcomes, quality, and length of life, as measured throughout the United States (CHR&R, 2023). The CMS data set focuses on the county and state levels' prevalence, use, and spending on chronic diseases (CMS, 2023). The combined data set contains records for 3,142 counties compared to the a priori minimum sample size of 172 counties.

Instrumentation and Operationalization of Variables

The current proposed cross-sectional study aims to evaluate the effects of SDoH on ADRD prevalence in the U.S. context of T2DM and AH. To these effects, this study evaluates already operationalized variables of population-level characteristics (Lau, 2017; Setia, 2016), most often by population percentages, regarding demographics, socioeconomics, health behavioral factors, and chronic disease prevalence, often measured as population percentages obtained from the 2018 County Health Rankings & Roadmaps (2023) and the CMS, (2023) spatially joined data sets and herein considered as possible predictors for ADRD prevalence evaluated under the five domains of the SDoH framework (see Figures 1 and 2; Banerjee et al., 2021; Bhunia & Shit, 2019; CDC, 2022).

Outcome Variable

ADRD Prevalence (Outcome Variable). This is a numeric continuous interval/ratio variable that measures the county's population percentage that has been clinically diagnosed with ADRD.

Predictor/Independent Variables

Educational Attainment. Evaluated from the education access and quality, social and community, and economic Stability domains of the SDoH, lower educational attainment has been linked to cognitive decline, impairment, and memory loss, some of the known clinical signs of dementia. Moreover, years of formal education strongly correlate with better employment and economic growth, reduced psychosocial stress, and healthier behaviors (CHR&R, 2023).

High School Graduation Rate. This is a numeric continuous interval/ratio variable that measures the county's population percentage of a ninth-grade cohort that graduates from high school in a 4-year period.

Percentage of Adults 25–44 With Some College. This is a numeric continuous interval/ratio variable that measures the county's population percentage ages 25-44 that have some post-secondary school but have not achieved a degree.

Housing. Evaluated from the Neighborhood & Built Environment and Economic stability domains of the SDoH framework, there are two groups of measures that include (a) access to housing infrastructure, quality, and related access to quality foods, and (b) household-related health behaviors.

Percentage of Population with Severe Housing Problems: This is a numeric continuous interval/ratio variable that measures the county's percentage of households with at least one of the following housing problems: overcrowding, high costs, lack of kitchen facilities, or lack of plumbing installations.

Percentage of Uninsured: This numeric continuous interval/ratio variable measures the county's percentage of adults <65 who lack health insurance.

FEI: This numeric continuous interval/ratio variable measures the county's indexed (0 – 10) factors contributing to a healthy food environment and food access, where 0 is the worst and 10 represents the best FEI.

Percentage of Food Insecure: This numeric continuous interval/ratio variable measures the county's percentage of the population who lack adequate access to food. FI is inversely related to the FEI.

Percentage of Rural: This numeric continuous interval/ratio variable measures the county's percentage of population living in rural areas.

Mental Health Providers Rate: This is a numeric continuous interval/ratio variable that measures the county's ratio of population to mental health providers servicing the county that specific year.

Age-Adjusted Mortality: This numeric continuous interval/ratio variable measures the county's age-adjusted number of deaths of residents <75 per 100,000 population.

Healthcare costs: This numeric continuous interval/ratio variable that measures the county's average household expenditure in dollars of health care-related expenses.

Chlamydia Rate: This is a numeric continuous interval/ratio variable that measures the county's number of newly diagnosed chlamydia cases per 100,000 population.

Percentage of Smokers: This is a numeric continuous interval/ratio variable that measures the county's age-adjusted population percentage of adults who are current smokers for the specific year.

Percentage of Obese: This is a numeric continuous interval/ratio variable that measures the county's age-adjusted population percentage of the adults 18 years of age or older with a body mass index greater than or equal to 30 kg/m^2.

Environmental Pollution. Evaluated from the neighborhood and built environment, social and community, and economic stability domains of the SDoH this

study uses U.S. Environmental Protection Agency-defined average daily particulate matter (PM2.5).

Average Daily Particulate Matter (PM2.5). This numeric continuous interval/ratio variable measures the county's average daily density of fine particulate matter in micrograms per cubic meter (PM2.5).

Mediator Variable

Income. Evaluated from the Neighborhood and Built Environment, Social and community, and Economic Stability domains of the SdoH this study ponders:

Median Household Income. This numeric continuous interval/ratio variable measures the county's population income where half of households earn more and half of households earn less. MHI points to income and poverty both related to health dynamics and related outcomes.

Income Ratio. This numeric continuous interval/ratio variable that measures the county's ratio of household income 80th to the 20th percentile. Which represents income inequality and points to socioeconomically derived disparities.

20th Percentile of Income. This numeric continuous interval/ratio variable measures the county's population percentage living under the lower 20th percentile of income. Which represents poverty and points to socioeconomically derived disparities and inequalities affecting human development, economic growth, health dynamics, and related outcomes.

Health Factors Rank and Health Outcomes Rank

Other SdoH that affect or are affected by educational attainment, income, housing, and air pollution include the county's health factors rank and health outcomes rank, both of which provide a measure of people's ability to promote better health dynamics and related outcomes.

- Health factors rank: This numeric continuous interval/ratio variable measures the county's ranking in factors promoting health compared to the rest of the nation's counties.
- Health outcomes rank: This numeric continuous interval/ratio variable measures the county's ranking of positive health outcomes compared to the rest of the nation's counties.

Chronic Diseases

Evaluated from all five domains of the SdoH (education access and quality, health care access and quality, neighborhood and built environment, social and community context, and economic stability) this study contemplates:

- T2DM prevalence (moderator variable): This study ponders T2DM prevalence measure as a moderator variable in the association between SDOH and ADRD prevalence. To these effects, T2DM exacerbates the adverse effects that the SdoH are known to have on ADRD and other chronic disease outcomes. T2DM prevalence is a numeric continuous interval/ratio variable that measures the county's percentage of the population diagnosed with T2DM in a specific year.

- AH (covariate): This study uses AH prevalence measure based on the standard definition of blood pressure measures ≥ 140/90 mmHg as the threshold to diagnose AH. It is a covariate as it influences ADRD prevalence, development, and onset outside of the SDOH or T2DM association with ADRD prevalence.
- SZ and Other psychotic disorder prevalence (covariate): This numeric continuous interval/ratio variable measures the county's population percentage diagnosed with SZ during a specific year. SZ is a known concurrent comorbidity to T2DM and AH.
- OP prevalence (covariate): This numeric continuous interval/ratio variable measures the county's population percentage diagnosed with OP during a specific year. OP is a known concurrent comorbidity to T2DM and AH.

Confounding Variables (Age, Gender, and Race/Ethnicity)

Age. A continuous ratio/interval level variable. Thus a confounding effect is expected from this variable in the evaluation of the predictors-outcomes relationships in all three RQs. Hence, due to the nature of the evaluated disease outcomes and related predictors, age has been broken into two major groups, < 65 and ≥ 65.

Gender. A nominal dichotomous (female, male) categorical variable which often renders a confounding effect on the outcome and predictors associations. Thus, controlling for gender, the regression models use the percentage of the female population per U.S. county.

Race/Ethnicity. A nominal/categorical variable which, based on ethnicity and

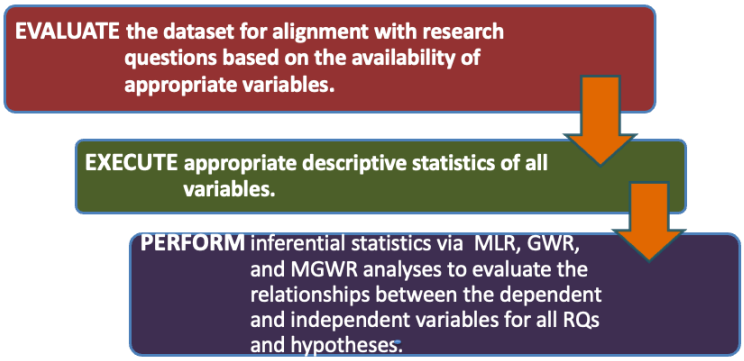
origin (non-Hispanic Black, non-Hispanic White, Hispanic/Latino, non-Hispanic Asian, Native Hawaiian/Other Pacific Islander, and AIAN) often renders a confounding effect on the outcome and predictors associations. This study attempts to control for race/ethnicity by accounting for the percentage of population distribution among the above-referenced racial/ethnic groups.

Data Analysis Plan

'For data cleaning and statistical analysis, I used Microsoft Excel and IBM's SPSS v.28 obtained through Walden University as well as spatial analysis software, which I obtained from multiple vendors. The spatial analysis software I used included ArcGIS Online and ArcGIS Pro 3.2 from Environmental Systems Research Institute and MGWR 2.2 from the SPARC of ASU. I used this software to evaluate the associations between ADRD prevalence and SdoH (educational attainment, income, housing, and pollution) in the United States in the context of T2DM and AH. I performed multiple linear regression, geographically weighted regression (GWR), and multiscale geographically weighted regression (MGWR). I data sets were evaluated for research alignment, one looking for the available required data and variables to address this dissertation's RQs and related hypotheses, and two, descriptive statistics of all involved variables will be performed to understand better the data type and alignment. Finally, inferential geospatial analysis and related statistics will be performed to address the established RQs and related hypotheses (see Figure 5).

Figure 5

Data Analysis Plan Flow Diagram



Statistical Analysis

This dissertation evaluates the associations between SDoH and ADRD prevalence in the U.S. context of T2DM and AH. As such it recognizes SDoH, based on the CDC's (2022) definition and SDoH Framework, as spatially and temporally varying relationships. Thus, the GWR and MGWR, both derived from the LR–OLS-fitted model as the most appropriate statistical methods for respectively addressing and testing the set forth RQs and related hypotheses (Boakye et al., 2022; Bonzani et al., 2023; Brunsdon et al., 1998; Charlton et al., 2009; de Bellefon & Floch, 2018; Fotheringham et al., 2003; Fotheringham et al., 2017; Fotheringham et al., 2023; Iyanda et al., 2020; Oshan et al., 2020; Raymundo et al., 2021; Rzasa & Ciski, 2022). These statistical methods are explained below.

Linear Regression

The LR model assumes or models a linear relationship between the outcome and related predictors. Thus it assumes the following general form:

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} \ldots \beta_n x_{ni} + \varepsilon_i \quad \textit{for } i=1,\ldots n. \textit{ (General Form)}$$

Or its simplest form: $y_i = \beta_0 + \beta_1 x_i + \varepsilon_i$ **…. *for i=1,…n.***

Where: y_i is the outcome or response variable, measured at locItion i, x_i is the predictor/explanatory, or independent variable, ε is the error dependency term. Where the parameter estimates (β) are considered stationary or constant, such that ($\beta_0 = \beta_1 = \beta_2 = \ldots\beta_n = \beta$) relationship effects throughout the modeled process over a constant space, and the value of $-n\,(y_i - \hat{y}_i)^2$ is minimized over the n observations in the data seI.

$\hat{y}_i$ is the predicted or fitted value for the i^{th} observation, given the i^{th} value of–**x**.

$(y_1 - \hat{y}_i)$ is the residual for the i^{th} observation. Residuals should be both, independent and drawn identically from a Normal Distribution with a mean of zero.

Thus, a measure of the goodness of fit is given by R^2 which represents the proportion of the variation in the dependent variable explained by the model's independent variable. In other words, it informs the researcher of how well does the model fits the data and provides an idea of predicting a model's outcome based on a specific independent variable input. The LR model is fitted through uares (OLS) and its parameter estimates or "β" coefficients are obtained from OLS through matrix operations:

$$\hat{\boldsymbol{\beta}} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{Y}$$

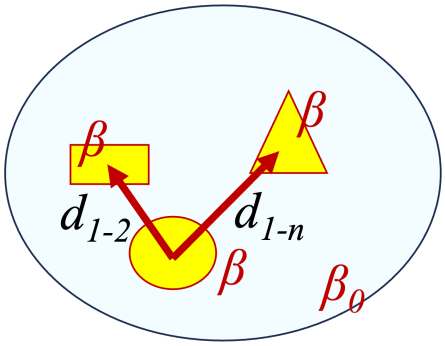
Where $\hat{\boldsymbol{\beta}}$ is the vector of estimated parameters, **X** is the design matrix of independent variables values and a column of ones, **Y** is the vector of observed values, and $(\mathbf{X}^T \mathbf{X})^{-1}$ is the inverse of the variance-covariance matrix.

Thus, LR posits the difficulty that non-constant relations can only be statistically observed through the residuals of the LR model by mapping the residuals to identify

potential spatial patterns, evaluating a statistical autocorrelation for the residuals, or, attempting to model the error dependency (ε_i) with various types of spatial regression models.

Figure 6

The Linear Regression Model Assumes constant β Effect Regardless of Spatiotemporal Differences.



Geographically Weighted Regression

GWR is a local spatial statistical technique based on the MLR model fitted by the OLS model. GWR is used to analyze spatial and temporally varying relationships (i.e., SDoH, disease outcomes, and temperature). In GWR, these spatially variable relationships are assumed to vary at a constant rate with respect to the distance from a specific reference point of measurement. GWR also assumes that the strength of association between the observed spatially varying relationships decreases as the distance between observation points increases (Brunsdon et al., 1998; Charlton et al., 2009; de Bellefon & Floch, 2018; Fotheringham et al., 2003).

The GWR incorporates local non-stationary (varying) relationships in the model to account for their related spatial and temporal variations.

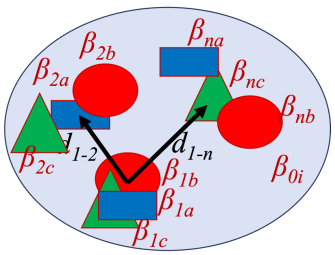
$$y_i(u) = \beta_{0i}(u) + \beta_{1i}(u)\, x_{1i} + \beta_{2i} I\, x_{2i} + \ldots \beta_{mi}(u)\, x_{mi}$$

Where **x** has **m** independent variables.

The GWR version of the OLS regression model assumes that the strength and direction of the relationship between a dependent variable and its predictors may be modified by contextual factors. The strength of association between a dependent variable and its predictors reduces with distance. The rate of change of the association with respect to distance between outcome and observation points (bandwidth) is constant. Observations should be independent of one another. And Spatial heterogeneity which questions the null hypotheses of homogeneity (All modeled relationships are the same throughout the area of analysis) (Brunsdon et al., 1998; Charlton et al., 2009; Fotheringham et al., 2003). To these effects, spatial dependence, and more significantly spatial dependence of the Residuals often leads to inefficient estimate parameters with large standard errors distorting the effects of these parameters (Tobler,1970).

Figure 7

The Geographically Weighted Regression (GWR) Model



The GWR model allows for incorporating spatially overlapping relationships (constant and varying) by location at a constant rate of change. $\beta_{1a} > \beta_{2a} > \ldots > \beta_{na}$, where $d_{1\text{-}n} > \ldots d_{1\text{-}2}$ are measured from location 1.

In the local GWR model: $y_i(u) = \beta_{0i}(u) + \beta_{1i}(u)\, x_{1i} + I(u)\, x_{2i} + \ldots \beta_{mi}(u)\, x_{mi}$

The estimated parameters vector is obtained similarly to the above OLS approach:

$$\hat{\beta} = [X^T W(u) X]^{-1} X^T W(u) Y$$

Where the $W(u)$ matrix contains the geographical weights in its leading diagonal and zeros in its off-diagonal elements.

Figure 8

The Weighting Matrix.

$$W(u) = \begin{bmatrix} w_1(\mathbf{u}) & 0 & 0 & 0 \\ 0 & w_2(\mathbf{u}) & 0 & 0 \\ 0 & 0 & \ldots & 0 \\ 0 & 0 & 0 & w_n(\mathbf{u}) \end{bmatrix}$$

The geographically weighted regression (Charlton et al., 2009). Based on the spatial weighting function, Weights "$w_i(\mathbf{u})$" are computed from a weighting scheme (kernel). A number of kernels are possible, a typical kernel has a Gaussian shape:

Figure 9

Computation of Geographical Weights.

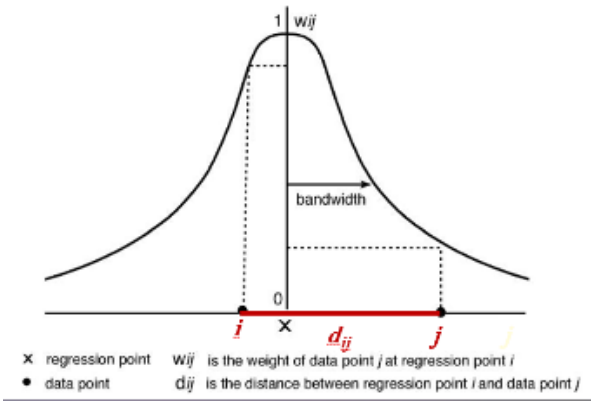
$$w_i(\mathbf{u}) = e^{-0.5\left(d_i(\mathbf{u})/h\right)^2}$$

Source: Geographically weighted regression. White paper. Charlton et al., 2009

Where: $w_i(\mathbf{u})$ is the geographical weight of the i^{th} observation relative to the location **u**, and $d_i(\mathbf{u})$ is the distance between the i^{th} observation and location **u**; and h is the bandwidth.

Figure 10

The Spatial Weighting Function



The Spatial Weighting Function follows a normal distribution of the regression residuals. Where x is the regression point wij is the weight of data point j at regression point i, dij is the distance between regression point i and data point j. Adapted from Propastin et al. (2008).

The distances $d_i(\mathbf{u})$ are generally Euclidean when using or projected Cartesian coordinates (i.e., longitude, latitude) and Great Circle distances when spherical coordinates are used. The bandwidth in the kernel is expressed in the same units as the coordinates used. As the bandwidth increases, the weights approach unity and the local GWR model approaches the global OLS fitted model (Charlton et al., 2009; Fotheringham et al., 2003).

In GWR, the goodness of fit measure is given by the corrected Akaike Information Criterion ($\mathbf{AIC_c}$) rather than the $\boldsymbol{R^2}$ used in LR. The AICc informs of the measured relative distances (Kullback-Leibler information distance) between the fitted model and the unknown "true" model. The $\boldsymbol{R^2}$ measured in GWR is often larger than that

of an LR. Hence, the $\mathbf{AIC_c}$ and the $\mathbf{R^2}$ in GWR provide greater statistical power (Charlton et al., 2009; Fotheringham et al., 2003; Hurvich et al, 1998).

Charlton et al. (2009) pointed out that the effective number of parameters in the model can be large and not necessarily an integer. This measure depends on the number of independent variables and the bandwidth However, it enables the evaluation the model's fit to the data. Moreover, in GWR, the **AIC** can be computed through the following:

Figure 11

The Akaike Information Criterion Formula (Hurvich et al, 1998).

$$AIC_c = 2n\log_e(\hat{\sigma}) + n\log_e(2\pi) + n\left(\frac{n + tr(\mathbf{S})}{n - 2 - tr(\mathbf{S})}\right)$$

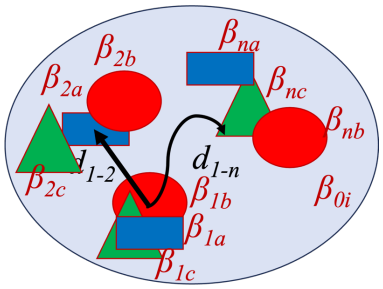
Multiscale Geographically Weighted Regression

MGWR is a refinement of the original GWR technique. MGWR allows for incorporating spatially overlapping relationships where the coefficients of the predictor variables (estimated parameters) vary across space at a non-constant rate of change. In MGWR, spatially varying relationships are not assumed to vary at a constant rate with respect to the distance from a specific reference point of measurement. Thus, each predictor variable may operate at a different spatial scale. MGWR also assumes that the strength of association between the observed spatially varying relationships decreases as the distance between observation points increases. The most significant benefit of the MGWR refinement lies in the reduction of statistical standard error and increased statistical power (Boakye et al., 2022; Bonzani et al., 2023; Fotheringham et al., 2017;

Fotheringham et al., 2023; Iyanda et al., 2020; Oshan et al., 2020; Raymundo et al., 2021; Rzasa & Ciski, 2022).

Figure 12

The Multiscale Geographically Weighted Regression (MGWR) Model



MGWR allows for incorporating spatially overlapping relationships (constant and varying) by location at different Rates of change. β1a > β2a >… > βna, where d1-n > …d1-2 are measured from location 1

MGWR It is a local regression model that allows the coefficients of the predictor variables (estimated parameters) to vary across space. Each predictor variable may operate at a different spatial scale. The strength of association between a dependent reduces with distance. The rate of change of the association with respect to distance (bandwidth) is not constant. The neighborhood (bandwidth) of a predictor variable determines the features used to estimate the estimated parameter "β coefficient" of that predictor or explanatory variable in the LR model fitted at a target feature (Fotheringham et al., 2017).

In MGWR, the goodness of fit measure is also given by the corrected Akaike Information Criterion (**AIC_c**) as in GWR. The difference or benefgit of MGWR comes with the regression model incorporation of varying coefficients of the predictor variables

(estimated parameters) at non-constant rates across space and different scales. This improvement in the model renders less standard error and greater statistical power than GWR and MLR.

Furthermore, the effect size can be calculated as follows:

Effect size = $(R^2) / (1-R^2)$

To these effects, using the Adj R^2 values from GWR or MWR rather than that of MLR, renders a more significant effect size by an order of magnitude. Thus pointing to increased statistical power of the MGWR or GWR models.

For example:

Using the 2018 County Health Ranking Data set lets evaluate the association between Population percentage of Diabetics and the SDoH as explanatory variables including percentage of smokers, percentage of obese, FEI, percentage of physically inactive, percentage with access to exercise opportunities, percentage of uninsured, gra^{du}ation rate, 20th percentile income, average daily PM2.5, and percentage of food insecure in the United States by county. The following results were obtained using ASU's MGWR 2.2:

Table 2

AICc and R^2 Values Computed Using ASU's MGWR 2.2 Software

US Population Measure Type by County	Population Percentage of Diabetics (T2DM)		Population Percentage of Diabetics (T2DM)	
	OLS	GWR	OLS	MGWR
Adj. R^2	0.69	0.808	0.69	0.808
AIC	4398.364	3331.444	4398.364	3331.444
Corr. AIC	4400.483	3367.618	4400.483	3367.618

For a sample size = 3414 counties, with 10 predictors, the Effect size (f^2) = (R^2) / (1-R^2) Using the OLS *is* f^2 = (0.69) / (1-0.69) = 2.22

When using GWR

f^2= (0.825) / (1-0.825) = 4.71 (more than two times stronger effect size than OLS/LR) which will render higher statistical power with a smaller sample size (see Figures 13–16).

Figure 13

Power Calculation for MLR/OLS Model Using G Power Statistics Software (f^2=0.0065)*

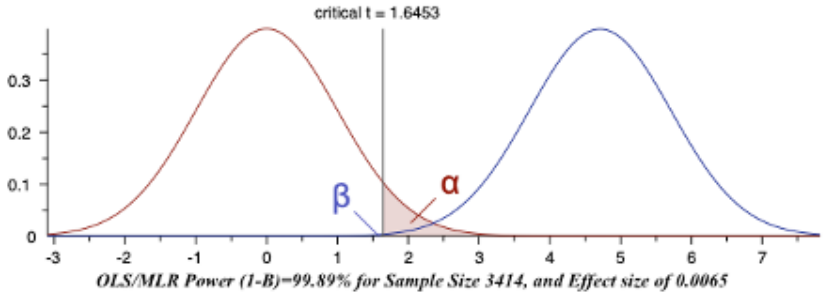
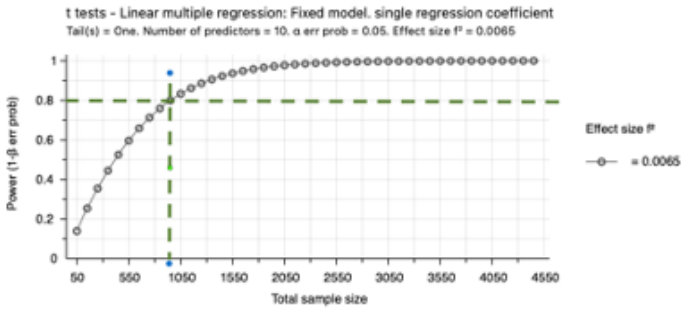


Figure 14

Statistical Power vs. Sample Size Plot



Given the number of predictors (10) and effect size f2=0.0065 Using G* Power Statistics Software. For power= 80% a minimum sample size of 1000 counties would be required.

Figure 15

F-Critical for Power Calculation for GWR or MGWR Models Using G Power Statistics Software Rendered $f^2=0.097 \sim 0.1$*

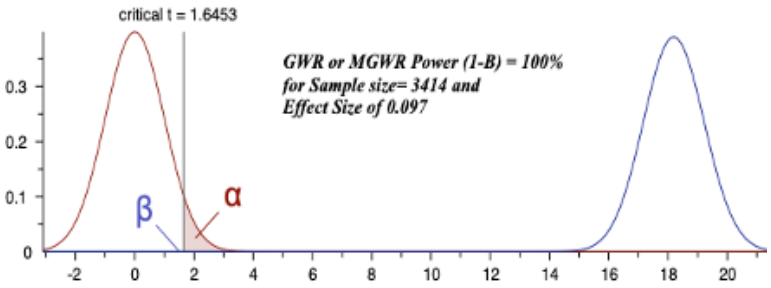
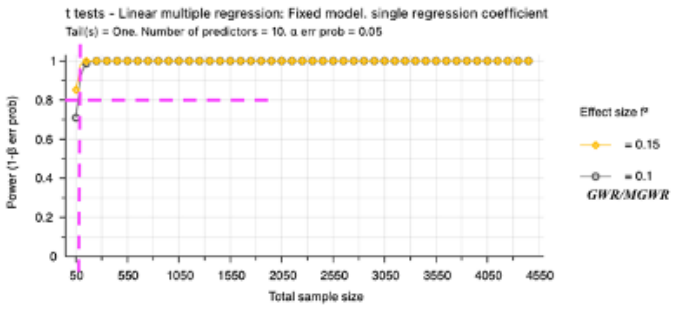


Figure 16

Statistical Power vs. Sample Size Plot



Given the number of predictors (10) and effect size f2=0.097 Using G* Power Statistics Software. For power= 80% a minimum sample size of only 50 counties would be required, 20 times less than the LR requirement on Fig. 13.

Data Cleaning and Screening Procedures

This study uses geospatially combined curated data from the 2018 CHR& R and CMS geocoded by U.S. county using FIPS codes. Although these data sets do not contain personally identifiable information data, screening was performed via Microsoft Excel and IBM SPSS, seeking possible duplicated records or additional data not pertaining to

county-level information for their removal. Moreover, screening helped identify age, ethnic/racial, and gender groups representing potential confounders. Finally, data screening and related cleaning was carried out to ensure the level of measurement of the above-identified variables for the association analysis between ADRD prevalence and SDoH in the U.S. context of chronic disease (IBM, 2021).

Since this dissertation evaluates the association between ADRD prevalence and SDoH (educational attainment, income, housing, and pollution) in the U.S. context of t2DM and AH, the following RQs and hypotheses are addressed in this study:

RQ1: Is there a statistically significant predictable relationship exist between SDoH (education attainment, income, housing, and pollution) and the prevalence of ADRD in the United States?

$H_0$1: No, there is no statistically significant predictable relationship between SDoH (education attainment, income, housing, and pollution) and the prevalence of ADRD in the United States.

H_a1: Yes, there is a statistically significant predictable relationship between SDoH (education attainment, income, housing, and pollution) the prevalence of ADRD in the United States.

RQ2: Is there a statistically significant predictable statistical relationship exist between T2DM and the prevalence of ADRD in the United States?

$H_0$2: No, there is no statistically significant predictable relationship between T2DM and the prevalence of ADRD in the United States.

H_a2: Yes, there is a statistically significant predictable relationship between T2DM and the prevalence of ADRD in the United States.

RQ3: Is there a statistically significant predictable relationship exist between AH and the prevalence of ADRD in the United States?

$H_0 3$: No, there is no statistically significant predictable relationship between AH and the prevalence of ADRD in the United States.

$H_a 3$: Yes, there is a statistically significant statistically predictable relationship between AH and the prevalence of ADRD in the United States.

RQ4: Is there a statistically significant predictable relationship exist between SDoH (education attainment, income, housing, and pollution) and the prevalence of ADRD in the U.S. context of T2DM and AH?

$H_0 4$: No, there is no statistically significant predictable relationship between SDoH (education attainment, income, housing, and pollution) and the prevalence of ADRD in the U.S. context of T2DM and AH.

$H_a 4$: Yes, there is a statistically significant predictable relationship between SDoH (education attainment, income, housing, and pollution) and the prevalence of ADRD in the U.S. context of T2DM and AH.

All four RQs and related hypotheses will be statistically evaluated using MLR, GWR, and MGWR with a set a priori power (1- β) of 80% and a statistical significance threshold of α=0.05 at a 95%CI. Nonetheless, based on the above calculations for minimum sample size of 172 counties (see Figures 3 and 4), the data set containing 3,142 signals a higher statistical power and potentially a greater statistical significance. The

available curated combined nationally representative data set also provides this study great validity and power. Odds ratios derived from each parameter coefficient will be calculated to better understand the influence of each variable in the specific related outcome.

Threats to Validity

This study uses curated secondary data from the 2018 CHR&R and CMS databases geospatially joined by U.S. counties using FIPS codes. Both CHR&R and CMS employ government agencies to collect and validate the acquired data, reducing potential external validity threats. However, in this case, the explicit population percentage by age group is only available for people >18, 25-44, and >65. The population percentage by gender is explicitly referenced for females only. These shortcomings represent potential threats to external validity. However, these obstacles can be easily overcome by computing the non-explicit values from the total county population and the available explicit measures. On the other hand, and as previously mentioned, the data set sample size (3,142 counties) is nearly 20 times larger than the minimum a priori calculated (172 counties), ensuring statistical power. The same approach applies to internal validity threats since the minimum calculated sample size accounts for a small effect size $f^2=0.1$, which should be overcome by both the actual sample size and GWR and MGWR statistical regression models (Bhunia & Shit, 2019; Olabode et al., 2019; Siedlecki, 2020; Wu et al., 2020). Hence, for all the above expl’ined, this study's use of curated nationally representative secondary data from CHR&R and CMS does not foresee any potential threats to validity.

Ethical Procedures

The CHJR&R and CMS are publicly available data sets whose curation processes have been performed, validated, and verified by the government agencies furnishing these data to CHR&R and CMS. As such, these data sets do not contain nor need to access personally identifiable information at any point in the dissertation. Hence, Walden University Institutional Review Board (IRB) permission to directly contact interviewees, interviewers, or data collectors was not necessary or required. To these effects, Walden University's IRB Approval was granted via Approval No. 11-21-23-0676766.

Summary

This quantitative cross-sectional design aims to evaluate the associations between ADRD prevalence and SDoH (educational attainment, income, housing, and environmental pollution) in the U.S. context of T2DM and AH. To these effects, this study uses a nationally representative and geospatially coded by U.S. counties FIPS codes data set from the 2018 CHR&R and CMS. This data set has 3,142 records available for statistical analysis using MLR, GWR, and MGWR compared to the a priori minimum calculated sample size of 172 counties using an a priori power (1- β) of 80% and a statistical significance threshold of $\alpha=0.05$ *at a 95%CI*.

Previous studies have evaluated the association of ADRD prevalence, development, and onset concerning T2DM or AH separately and apart from educational attainment, income, housing, or environmental pollution. However, as the present dissertation posits, these associations have not yet been evaluated from the SDoH and contextual geographic distribution or in conjunction. Moreover, this dissertation ponders

the concurrent comorbidity context of T2DM and AH where SZ, OP, and even rheumatoid arthritis (RA) and depression find, if not a genesis, a conundrum of poverty and disease that must be addressed. Hence, this study may contribute to the epidemiology field knowledge and provide new avenues of research for culturally and socioeconomically contextual public health interventions to prevent or delay ADRD and the related disparities of the financial and health burdens these diseases impose, especially in lower income demographics and related economic minorities in the United States. Thus, this dissertation also seeks to reduce and eliminate health inequities and inequalities via a sustainable approach to social change that catalyzes human development with economic growth, empowering women in the community in a circular economy approach.

Chapter 4 focused on the statistical analysis of the combined curated data set using IBM-SPSS v.28 obtained through Walden University, spatial analysis software, namely, ArcGIS Online, ArcGIS Pro 3.2 from Environmental Systems Research Institute, and MGWR 2.2 from the SPARC of the ASU to address the posited RQs regarding ADRD prevalence and SDoH (educational attainment, income, housing, and pollution) in the United States in the context of T2DM, AH using MLR, GWR, and MGWR. Chapter 4 also provided a chapter summary of the above-mentioned analysis.

Chapter 4: Results

Introduction

In this study, I evaluated the associations between the prevalence of ADRD and SDoH (educational attainment, income, housing, and environmental pollution) in the U.S. context of T2DM and AH. To explore potential relationships, I used a quantitative cross-sectional design rooted in the SDoH framework (CDC, 2022) and involving geospatial and statistical analyses. The RQs and hypotheses for the study were as follows:

RQ1: Is there a statistically significant predictable relationship exist between SDoH (education attainment, income, housing, and pollution) and the prevalence of ADRD in the United States?

$H_0$1: No, there is no statistically significant predictable relationship between SDoH (education attainment, income, housing, and pollution) and the prevalence of ADRD in the United States.

H_a1: Yes, there is a statistically significant predictable relationship between SDoH (education attainment, income, housing, and pollution) and the prevalence of ADRD in the United States.

RQ2: Is there a statistically significant predictable statistical relationship exist between T2DM and the prevalence of ADRD in the United States?

$H_0$2: No, there is no statistically significant predictable relationship between T2DM and the prevalence of ADRD in the United States.

H_a2: Yes, there is a statistically significant predictable relationship between T2DM and the prevalence of ADRD in the United States.

RQ3: Is there a statistically significant predictable relationship exist between AH and the prevalence of ADRD in the United States?

$H_0$3: No, there is no statistically significant predictable relationship between AH and the prevalence of ADRD in the United States.

H_a3: Yes, there is a statistically significant statistically predictable relationship between AH and the prevalence of ADRD in the United States.

RQ4: Is there a statistically significant predictable relationship exist between SDoH (education attainment, income, housing, and pollution) and the prevalence of ADRD in the U.S. context of T2DM and AH?

$H_0$4: No, there is no statistically significant predictable relationship between SDoH (education attainment, income, housing, and pollution) and the prevalence of ADRD in the U.S. context of T2DM and AH.

H_a4: Yes, there is a statistically significant predictable relationship between SDoH (education attainment, income, housing, and pollution) and the prevalence of ADRD in the U.S. context of T2DM and AH.

In Chapter 4, I discuss the statistical analyses I used (MLR, GWR, and MGWR) to evaluate the RQs and hypotheses, and I present the results of my investigation.

Data Collection

I used two nationally representative samples of curated secondary data from 2018, geospatially joined and coded by US County: the CHR&R and the multiple chronic diseases data set from the CMS. A nationally representative sample was required because of the use of a cross-sectional design rooted in the SDoH framework to evaluate ADRD

prevalence at the county population level influenced by contextual SDoH, T2DM, and AH. To evaluate these effects, I acquired, as planned, the CHR&R and CMS data sets, which were readily available to the public for download. In accordance with the data analysis plan discussed in Chapter 3, I undertook data cleaning and preparation in three phases:

1. Verification and evaluation of data type and variables availability.
2. Removal of unnecessary variables and related data.
3. Geospatial join of data sets, per county name and U.S. FIPS codes, via ArcGIS Online.

Data Analysis

For the required geospatial and statistical analyses, GWR, MGWR, and MLR regression models were the most appropriate tests. I used an a priori statistical power of at least (1-β) = 80% and a statistically significant threshold alpha equal to 0.05 to determine the minimum required sample size, consistent with the literature (e.g., Bhunia & Shit, 2019; Cohen, 2013; Cohen et al., 2013; Cvetković Vega et al., 2021; Haijan-Tilaki, 2011; Lu et al., 2013). The minimum sample size was calculated using G*Power Statistics Software v. 3.1 through an F-test for MLR fixed model and R^2 deviation from zero. Based on this test for 28 predictors (degrees of freedom), $F(1,28) = 1.525$, the minimum sample size was 261 counties (the unit of analysis) for a minimum effect size $f^2 = 0.1$ using 28 predictors (see Figures 16 and 17). The nationally representative geospatially joined data sample available from CHR&R and CMS contained data for 3,142 counties, which should increase the statistical power (see Figure 17).

Figure 17

A Priori Power F-Critical Calculation F(1, 28) = 1.525 for a Minimum Sample Size of 261 Counties

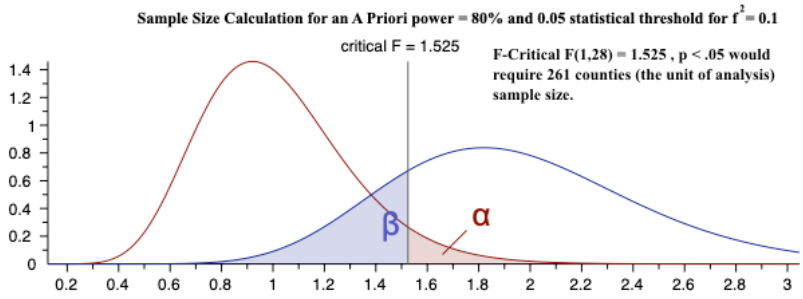
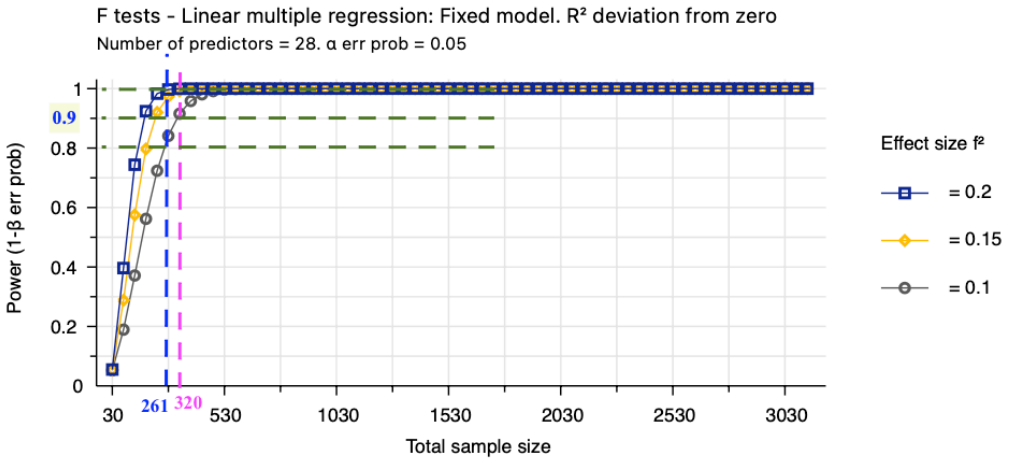


Figure 18

Minimum Sample Size vs. Power Calculation for F(1, 28) = 1.525, p< .05 and A Priori Power 80% and a f^2=0.1 Rendered (261 Counties)



Based on the above power, F-statistics, and sample size calculations for a minimum effect size $f^2 = 0.1$, the available curated and spatially joined sample size of 3142 counties correctly represents the U.S. counties population since the minimum required sample size is 261 counties.

Results

Descriptive Statistics

I computed descriptive statistics, using the joined data sets, for age and gender, race/ethnicity, and the SDoH.

Age and Gender

The U.S. County population distribution evaluation revealed a nearly 50%_50% split by gender, across all age brackets (see Table 3), except for the >65 group where women comprised approximately 54% and men 46% (see Table 4). Age and gender are confounding variables that will need to be controlled in the related statistical analysis.

Table 3

Descriptive Statistics of the 2018 US Counties Population Percent by Age (<45) and Gender

Descriptive Statistics of Population Percent by Age (<45) and Gender

		County Total Population Percentage <18	County Female Population Percentage <18	County Male Population Percentage <18	County Total Population Percentage 18-24	County Female Population Percentage 18-24	County Female Population Percentage 18-24	County Total Population Percentage 25-44	County Female Population Percentage 25-44	County Male Population Percentage 25-44
N	Valid	3142	3142	3142	3142	3142	3142	3142	3142	3142
	Missing	0	0	0	0	0	0	0	0	0
Mean		.2209	.1078	.1132	.0859	.0406	.0453	.2350	.1135	.1215
Std. Error of Mean		.00062	.00031	.00032	.00058	.00030	.00031	.00057	.00029	.00041
Median		.2207	.1075	.1132	.0782	.0368	.0410	.2326	.1128	.1170
Mode		.25	.10	.09[a]	.06[a]	.04	.03[a]	.26	.10[a]	.11
Std. Deviation		.03471	.01729	.01784	.03249	.01656	.01743	.03212	.01606	.02319
Variance		.001	.000	.000	.001	.000	.000	.001	.000	.001
Skewness		.372	.364	.381	3.879	3.864	4.200	.697	.495	2.220
Std. Error of Skewness		.044	.044	.044	.044	.044	.044	.044	.044	.044
Kurtosis		2.810	2.737	2.750	21.605	21.541	30.358	2.122	2.026	9.612
Std. Error of Kurtosis		.087	.087	.087	.087	.087	.087	.087	.087	.087
Range		.42	.21	.21	.44	.22	.30	.29	.16	.26
Minimum		.00	.00	.00	.00	.00	.00	.12	.04	.07
Maximum		.42	.21	.21	.44	.22	.30	.41	.21	.33

[a] Multiple modes exist. The smallest value is shown

The mean population percentages by county were *22.1%* for the <18 group, 8.6% for the 18-24 group, *23.5%* for the 25-44 group (Table 3), and *26.6%* for the 45-64 group, adding up to *80.7%* for the <65 group, and *19.3%* for the ≥65 group (Table 4).

Table 4

Descriptive Statistics of the 2018 US Counties Population Percent by Age (≥ 45) and Gender

Descriptive Statistics of Population Percent by Age (45 and Over) and Gender

		County Total Population Percentage 45-64	County Female Population Percentage 45-64	County Male Population Percentage 45-64	County Total Population Percentage <65	County Female Population Percentage <65	County Male Population Percentage <65	County Total Population Percentage >65	County Female Population Percentage >65	County Male Population Percentage >65
N	Valid	3142	3142	3142	3142	3142	3142	3142	3142	3142
	Missing	0	0	0	0	0	0	0	0	0
Mean		.2656	.1332	.1323	.8074	.8962	.9113	.1926	.1038	.0887
Std. Error of Mean		.00048	.00026	.00028	.00084	.00043	.00043	.00084	.00043	.00043
Median		.2681	.1348	.1327	.8107	.8969	.9145	.1893	.1031	.0855
Mode		.25[a]	.13	.12[a]	.42[a]	.88[a]	.89[a]	.05[a]	.08[a]	.07[a]
Std. Deviation		.02689	.01446	.01561	.04710	.02393	.02419	.04710	.02393	.02419
Variance		.001	.000	.000	.002	.001	.001	.002	.001	.001
Skewness		-.568	-.729	.378	-.749	-.606	-.997	.749	.606	.997
Std. Error of Skewness		.044	.044	.044	.044	.044	.044	.044	.044	.044
Kurtosis		2.623	1.640	5.617	2.374	2.935	2.572	2.374	2.935	2.572
Std. Error of Kurtosis		.087	.087	.087	.087	.087	.087	.087	.087	.087
Range		.33	.13	.22	.53	.27	.25	.53	.27	.25
Minimum		.10	.05	.05	.42	.70	.73	.05	.03	.02
Maximum		.43	.18	.27	.95	.97	.98	.58	.30	.27

[a]. Multiple modes exist. The smallest value is shown

The 2018 county mean age was 40.3 years for women and *42.9* years for men. The general population's county mean age was *41.6* years (see Table 5).

Table 5

The 2018 US County Mean Age by Gender.

Descriptive Statistics of Counties Population Age by Gender

		US County Mean Age of Total Population	US County Mean Age of Male Population	US County Mean Age of Female Population
N	Valid	3142	3142	3142
	Missing	0	0	0
Mean		41.5661	40.2812	42.9384
Std. Error of Mean		.09616	.09609	.09767
Median		41.4000	40.0000	43.0000
Mode		41.20	38.40	42.10
Std. Deviation		5.39009	5.38594	5.47499
Variance		29.053	29.008	29.976
Skewness		.143	.310	-.026
Std. Error of Skewness		.044	.044	.044
Kurtosis		.793	.901	.679
Std. Error of Kurtosis		.087	.087	.087
Range		45.50	45.80	45.60
Minimum		22.30	21.50	22.50
Maximum		67.80	67.30	68.10

Race/Ethnicity

The U.S. counties' mean population percentages by race/ethnicity were 8.9% for non-Hispanic Black, 2.3% for AIAN, 1.5% for non-Hispanic Asians, 0.13% for Hawaiians and other Pacific Islanders, 9.3% for Hispanic/Latinos, and 76.6% non-Hispanic White (see Table 6). Race/ethnicity is a confounding variable that will need to be controlled in the related statistical analysis.

Table 6

Descriptive Statistics for Race/Ethnicity

Descriptive Statistics for Age/Ethnicity

		Population Percent African-American (non-Hispanic Black)	Population Percent American Indian / Alaskan Native (AIAN)	Population Percent Asian	Population Percent Native Hawaiian & Other Pacific Islander	Population Percent Hispanic/Latino	Population Percent non-Hispanic White
N	Valid	3142	3142	3142	3142	3142	3142
	Missing	0	0	0	0	0	0
Mean		8.9425	2.3094	1.4856	.1349	9.2896	76.5843
Std. Error of Mean		.25531	.13774	.05101	.01757	.24373	.35836
Median		2.1750	.6100	.7000	.0600	4.1000	83.9900
Mode		.53	.34	.45	.03	1.58[a]	94.11[a]
Std. Deviation		14.31113	7.72066	2.85933	.98500	13.66175	20.08743
Variance		204.808	59.609	8.176	.970	186.644	403.505
Skewness		2.300	7.625	7.282	43.037	3.103	-1.206
Std. Error of Skewness		.044	.044	.044	.044	.044	.044
Kurtosis		5.256	66.312	74.560	2111.203	11.076	.852
Std. Error of Kurtosis		.087	.087	.087	.087	.087	.087
Range		85.15	93.07	44.27	50.00	95.75	95.17
Minimum		.00	.00	.00	.00	.50	2.81
Maximum		85.15	93.07	44.27	50.00	96.25	97.98

[a] Multiple modes exist. The smallest value is shown

The extreme leptokurtic distribution values observed for Asians, AIAN, and Hawaiians/other Pacific Islanders correspond to their lower percentages of population and geographic concentration (see Figures 19–24).

Figure 19

The US 2018 Distribution of the Asian Percent Population Correlates to a Leptokurtic (74.56) and Skewed (7.282) Distribution Converging With Table 6 and Figure 20.

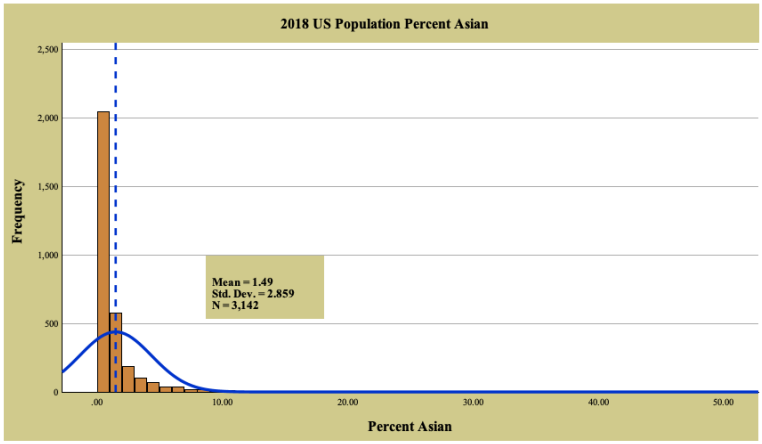


Figure 20

US 2018 Geographic Distribution of the Asian Percent Population Correlates to a Leptokurtic and Skewed Distribution Converging With Table 6 And Figure 19

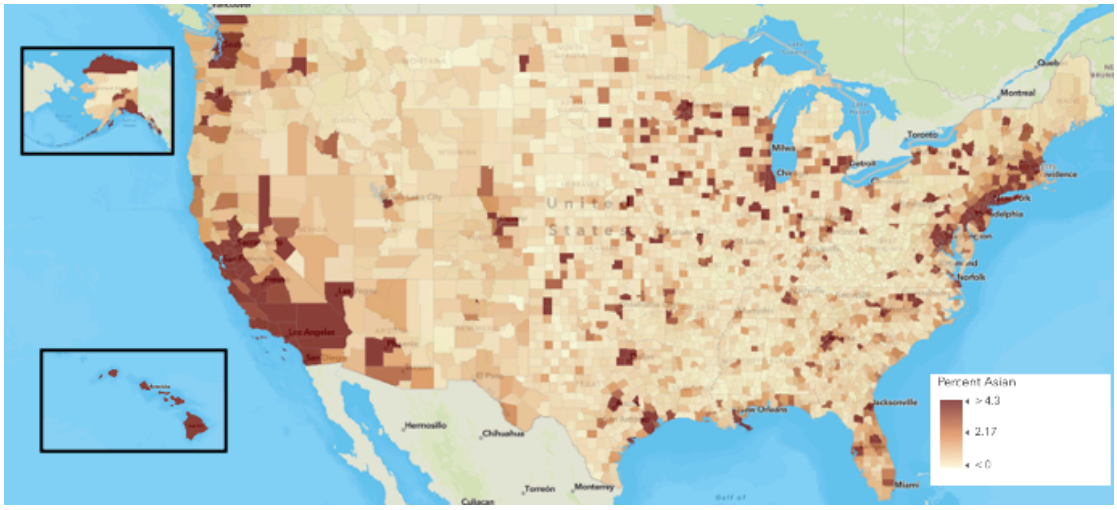


Figure 21

The US 2018 Distribution of the AIAN Population Percent Correlated to a Leptokurtic (2111.2) and Skewed (7.625) Distribution Converging With Table 6 and Figure 22

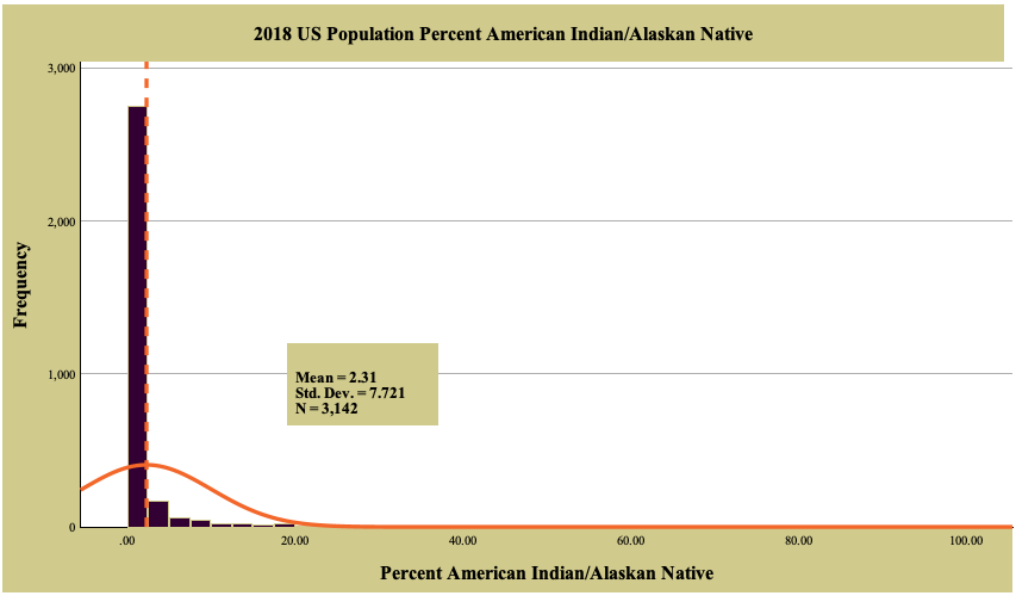


Figure 22

The US 2018 Geographic Distribution of the AIAN Population Percent Correlates to a Leptokurtic and Skewed Distribution Converging With Table 6 and Figure 21

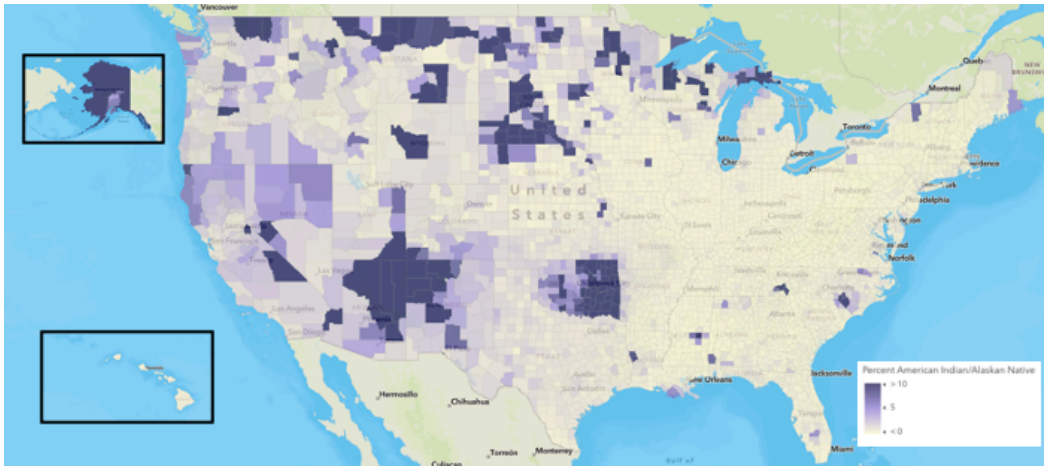
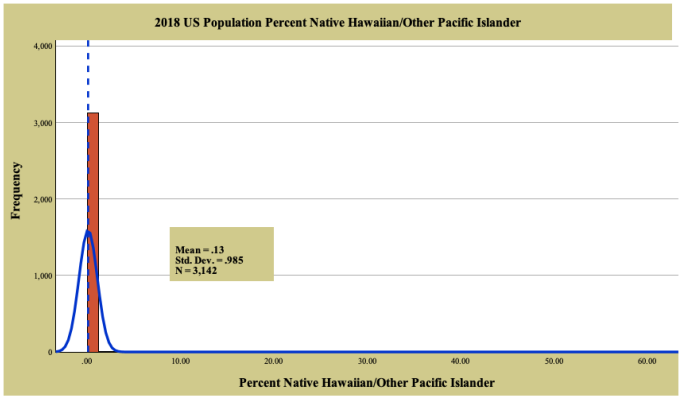


Figure 23

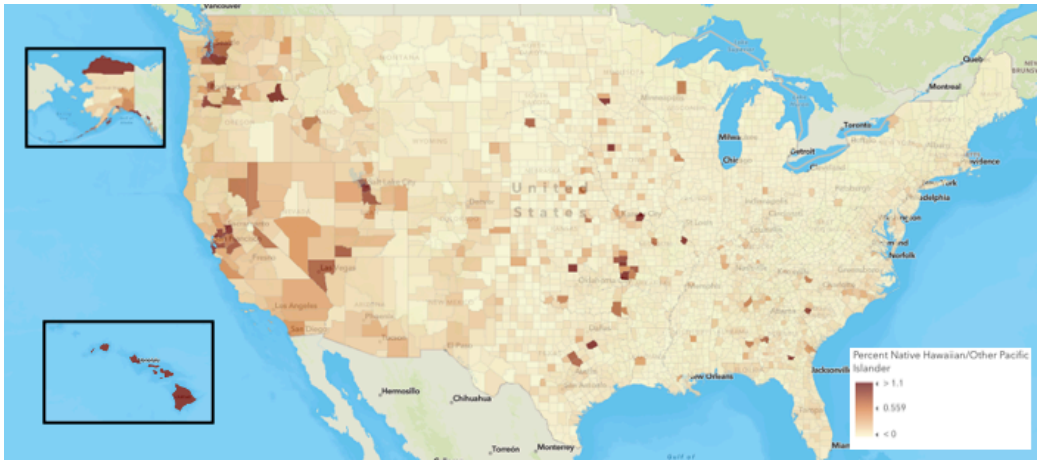
The US 2018 Geographic Distribution of Native Hawaiians/other Pacific Islander



The US 2018 Geographic Distribution of Native Hawaiians/other Pacific Islander Population Percent correlates to a leptokurtic (74.56) and skewed (43.037) distribution converging with Table 6 and Figure 24.

Figure 24

The US 2018 Geographic Distribution of Native Hawaiians/other Pacific Islander

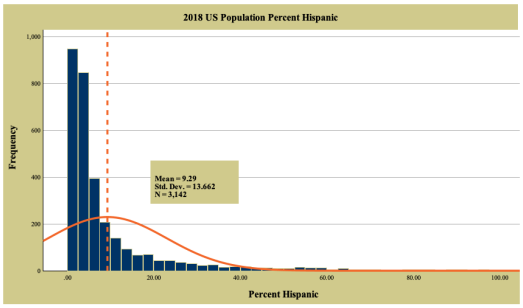


US 2018 Geographic Distribution of Native Hawaiians/other Pacific Islander population percent correlates to a leptokurtic and skewed distribution converging with Table 6 and Figure 23.

Populations of Hispanic/Latino origins, non-Hispanic Blacks, and non-Hispanic Whites comprise higher population percentages and are more widely distributed throughout the country, yet with historical geographic concentration (see Figures 25–30).

Figure 25

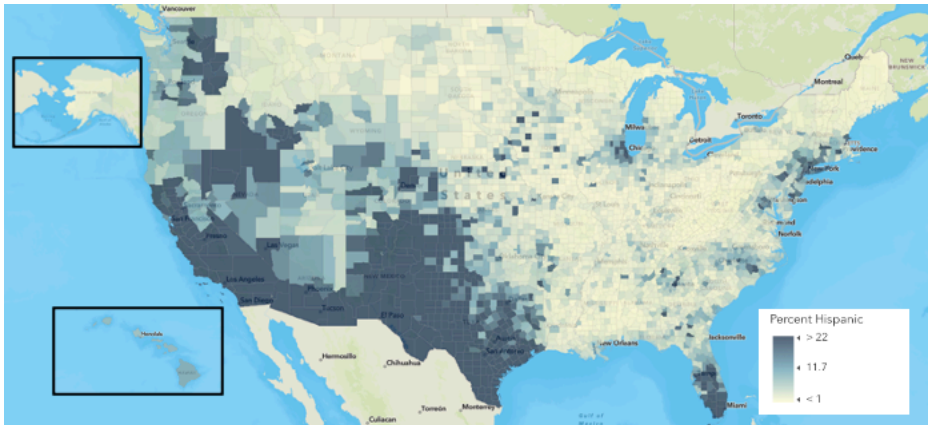
The US 2018 Geographic Distribution of Hispanic/Latino Population Percent



The US 2018 Geographic Distribution of Hispanic/Latino population percent correlates to a leptokurtic (11.076) and skewed (3.102) distribution converging with Table 6 and Figure 26.

Figure 26

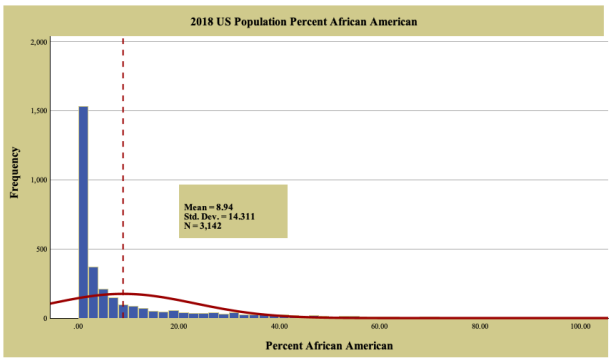
The US 2018 Geographic Distribution of the Latino Population Percent



The US 2018 Geographic Distribution of the Latino population percent correlates to a leptokurtic and skewed distribution converging with Table 6 and Figure 25.

Figure 27

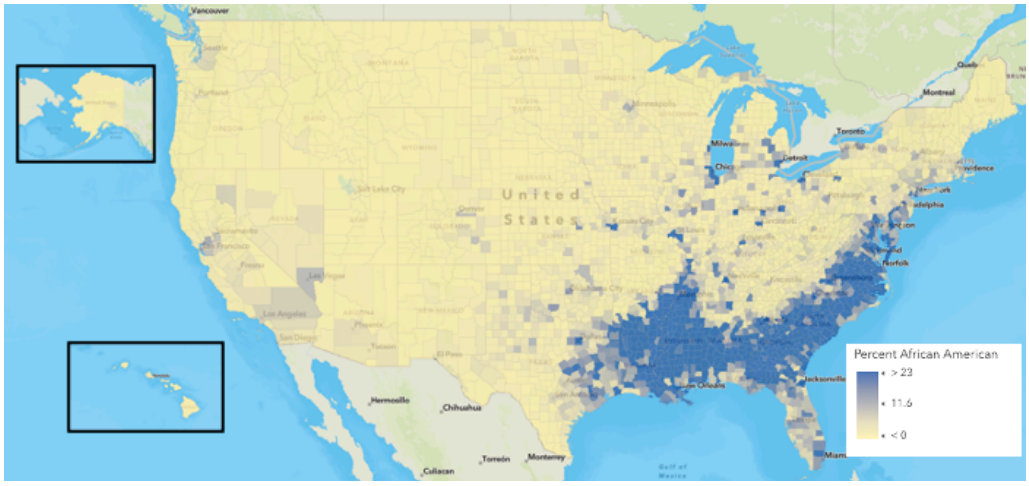
US 2018 Geographic Distribution of non-Hispanic Black Population Percent



US 2018 Geographic Distribution of non-Hispanic Black population percent correlates to a normal kurtosis (5.256) and skewed (2.3) distribution converges with Table 6 and Figure 28.

Figure 28

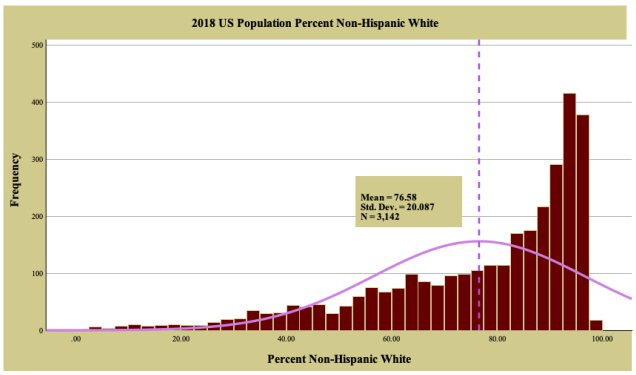
The US 2018 Geographic Distribution of non-Hispanic Black Population Percent



The US 2018 Geographic Distribution of non-Hispanic Black population percent correlates to a normal kurtosis and skewed distribution converging with Table 6 and Figure 28.

Figure 29

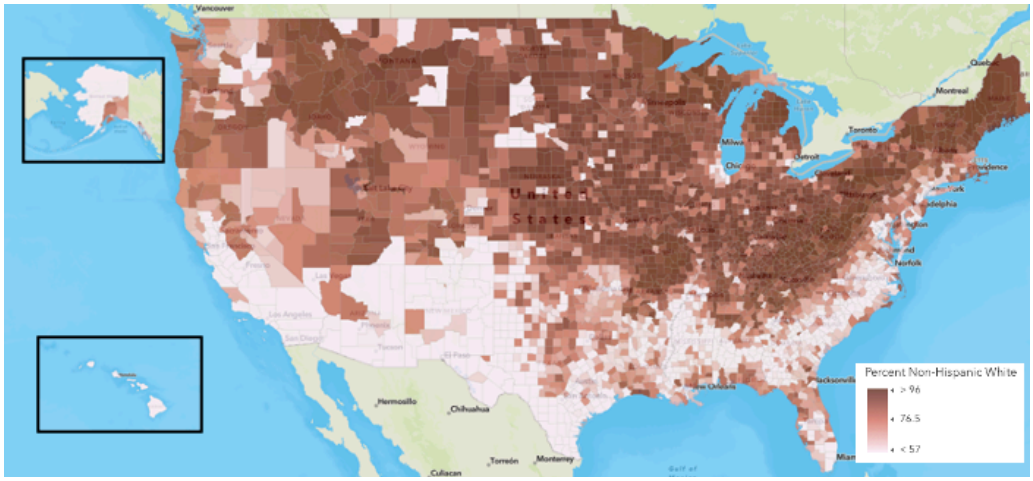
The US 2018 Geographic Distribution of the non-Hispanic White Population Percent



The US 2018 Geographic Distribution of the non-Hispanic White Population Percent correlates to a platykurtic (0.852) and negatively skewed (-1.203) distribution converging with Table 6 and Figure 30.

Figure 30

The US 2018 Geographic Distribution of the non-Hispanic White Population Percent



The US 2018 Geographic Distribution of the non-Hispanic White population percent correlates to a platykurtic and negatively skewed distribution converging with Table 6 and Figure 31.

The statistical analysis for race and ethnicity of Table 6, showing mean, skewness (the tendency of the distribution), and kurtosis (the concentration of the distribution near the mean), converges with the geospatial distribution evaluation of Figures 19-30 correlating to historical concentration and migration patterns of these racial/ethnic groups compared to non-Hispanic Whites.

Social Determinants of Health

The SDoH entail all nonmedical factors affecting health dynamics and related outcomes. The SDoH include the socio-political settings in which people are born, grow, work, live, and age, alongside the natural and built environment and the socioeconomics and social-political constructs that shape and condition daily life (CDC, 2022). Hence the geospatial evaluation of the SDoH relations to human health dynamics and related outcomes is presented below, before the evaluation of ADRD prevalence addressing RQ1 of this dissertation.

Housing. The evaluation of housing related SDoH descriptive statistics showed the mean population percentages as follows: 17.9% for smokers, 31.7% for obese, 14.1% for food insecure, 14.5% for people with severe housing problems, and 14.3% for uninsured adults. The mean FEI of 7.3/10, a 4.52mean income ratio (inequality), a 345/100,000 Chlamydia infection rate, a 393/100,000 Age-adjusted mortality rate, and a mean health care cost of $9,608 per household (see Table 7 and Figures 31–40).

Table 7

Descriptive Statistics of Housing Related SDoH.

Housing-related SDoH Descriptive Statistics

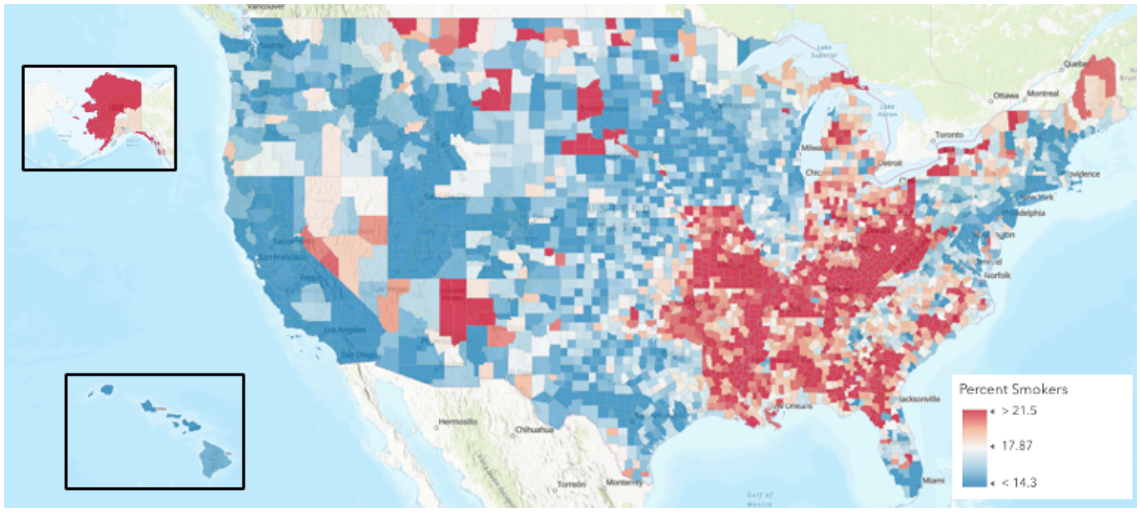
		Population Percent Smokers	Population Percent Obese	Food Environment Index	Population Percent Food Insecure	Income Ratio /Income Inequality	Chlamydia Infection Rate	Percent Population with Severe Housing Problems	Age-Adjusted Mortality	Percent Adults Uninsured	Health Care Costs
N	Valid	3142	3142	3142	3142	3142	3142	3142	3142	3142	3142
	Missing	0	0	0	0	0	0	0	0	0	0
Mean		17.8726	31.474	7.364	14.139	4.520	345.096	14.4618	393.015	14.2840	9608.72
Std. Error of Mean		.06530	.0805	.0235	.0756	.0133	4.4319	.08544	2.1886	.11157	27.939
Median		17.3200	31.800	7.600	13.600	4.400	291.650	13.9900	386.100	13.5650	9600.00
Mode		15.65[a]	32.2	7.8	13.4	4.5	.0	12.03[a]	.0	7.33[a]	0
Std. Deviation		3.66004	4.5141	1.3148	4.2360	.7442	248.4230	4.78948	122.6784	6.25362	1566.086
Variance		13.396	20.377	1.729	17.944	.554	61713.968	22.939	15049.991	39.108	2452626.384
Skewness		.818	-.371	-2.063	.922	1.005	2.286	1.968	.034	.784	-.112
Std. Error of Skewness		.044	.044	.044	.044	.044	.044	.044	.044	.044	.044
Kurtosis		2.494	.858	7.420	2.063	3.322	11.747	13.229	2.534	.607	3.989
Std. Error of Kurtosis		.087	.087	.087	.087	.087	.087	.087	.087	.087	.087
Range		36.01	35.0	10.0	34.5	8.9	2889.7	67.43	1142.6	43.40	19803
Minimum		6.74	12.8	.0	3.4	.0	.0	2.69	.0	.00	0
Maximum		42.75	47.8	10.0	37.9	8.9	2889.7	70.12	1142.6	43.40	19803

[a] Multiple modes exist. The smallest value is shown

Figure 31 shows a higher concentration of smokers in the red shaded areas, especially in the southeastern United States.

Figure 31

The US 2018 Geospatial Distribution of Smokers' Population Percent



The US 2018 geospatial distribution of smokers' population percent above and below the mean (17.87%). Red shades denote the smoking population above the mean.

Figure 32 shows a higher concentration in the bright-brown areas from the north through southeastern US. The US 2018 geospatial distribution of obesity population percent above and below the mean (31.47%). Bright-Brown shades denote the obese population above the mean.

Figure 32

The US 2018 Geospatial Distribution of Obesity Population Percent

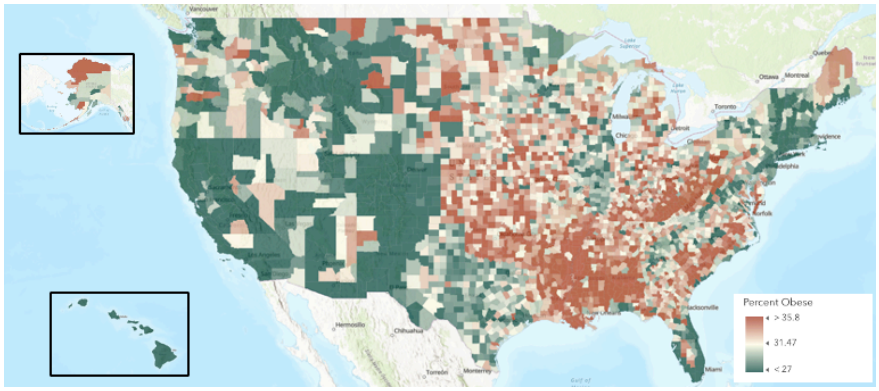


Figure 33 shows the geospatial distribution of the FEI in the United States. Burgundy shades point to areas of FEI lower than the national mean of 7.4, burgundy shades denote the FEI < the mean.

Figure 33

The US 2018 Geospatial Distribution of FEI

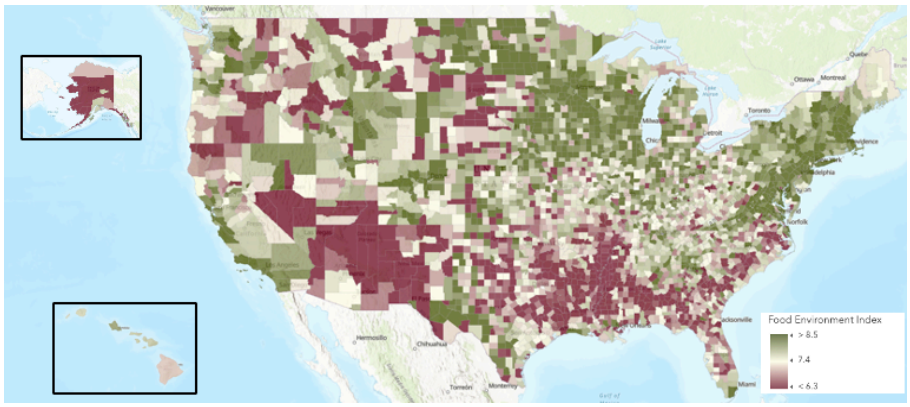


Figure 34 shows the geospatial distribution of the FI population above and below the mean (14.1%) in the United States. Red shades point to areas of FI population high than the national mean of 14.1% (i.e., southern, and southeastern United States).

Figure 34

The US 2018 Geospatial Distribution of Food Insecure (FI)

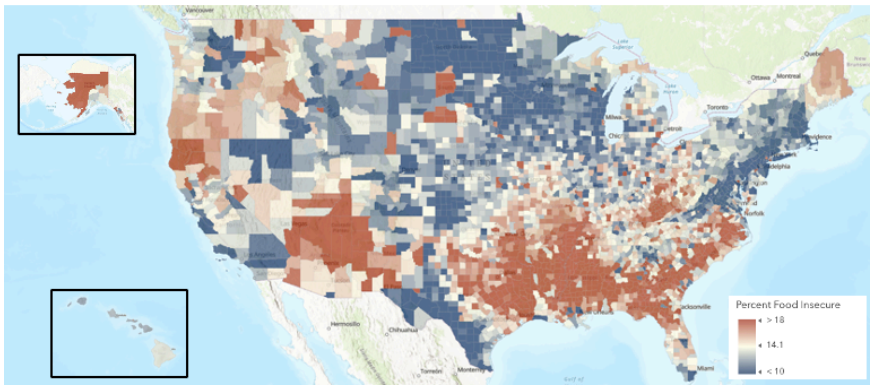


Figure 35 shows the geospatial distribution of income inequality (80th Percentile/20th Percentile) population above and below the mean (4.5) in the United States. Bright-brown shades point to areas of higher inequality than the national mean (i.e., southern, and southeastern United States).

Figure 35

The US 2018 Geospatial Distribution of Income Ratio or Income Inequality.

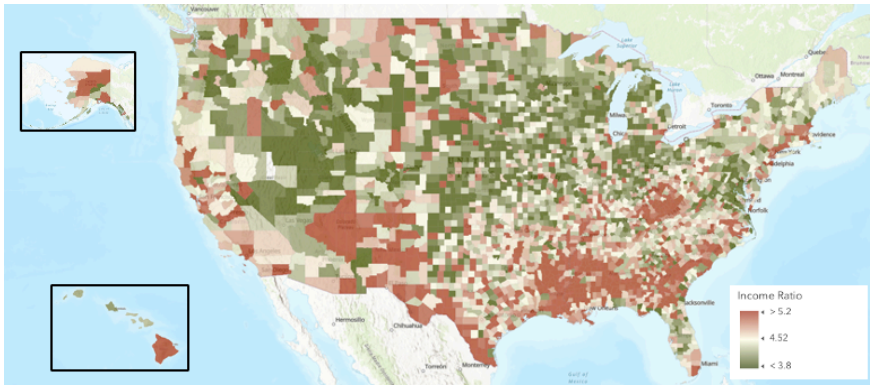


Figure 36 shows the geospatial distribution of Chlamydia infection rate in the U.S. population above and below the mean (364/100,000). Red shades point to areas of higher rate than the national mean (i.e., northcentral, southern, and southeastern United States).

Figure 36

The US 2018 Geospatial Distribution of Chlamydia Infection Rate

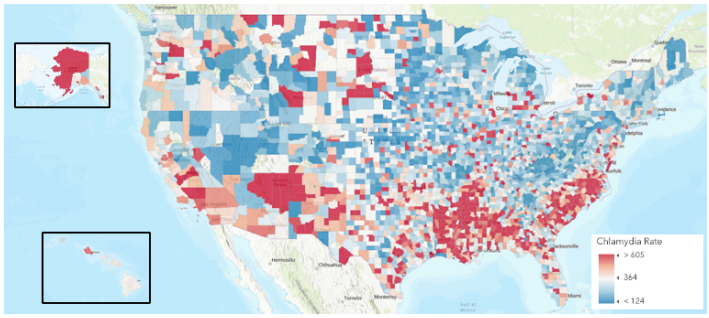


Figure 37 shows the geospatial distribution of the population with severe housing problems above and below the mean (14.4%) in the United States. Burgundy shades point to areas of higher population percentage with severe housing problems than the national mean (i.e., northwestern, western, southern, southeastern, and northeastern United States).

Figure 37

The US 2018 Geospatial Distribution of Severe Housing Problem Population Percent

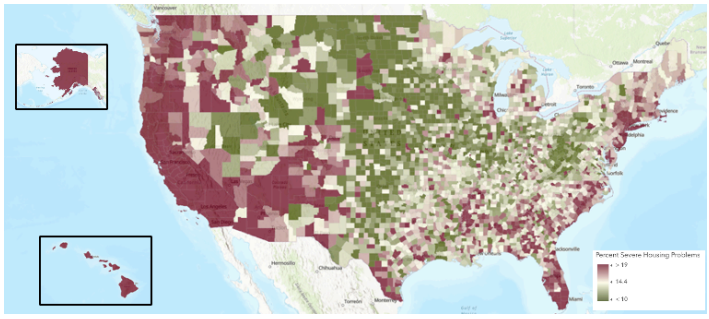


Figure 38 shows the geospatial distribution of the age-adjusted mortality rate above and below the mean (401/100,000) in the United States. Red shades point to areas of higher age-adjusted mortality rates than the national mean (i.e., northcentral, western, southern, and southeastern United States).

Figure 38

The US 2018 geospatial distribution of the Age-Adjusted Mortality Rate

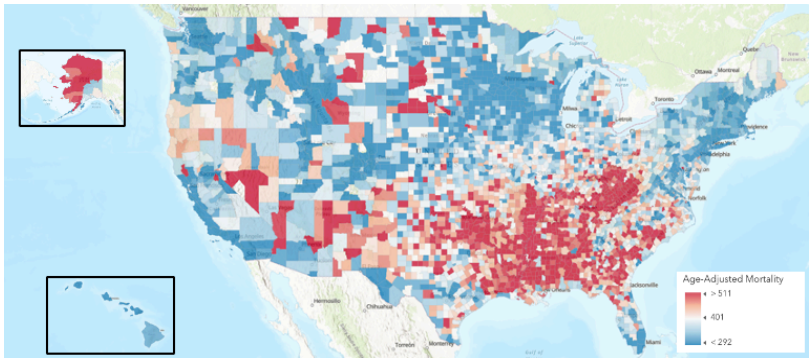


Figure 39 shows the geospatial distribution of the age-adjusted mortality rate above and below the mean (401/100,000) in the United States. Burgundy shades point to areas of higher age-adjusted mortality rates than the national mean (i.e., northcentral, western, southern, and southeastern United States).

Figure 39

The US 2018 Geospatial Distribution of Uninsured Adults Percent

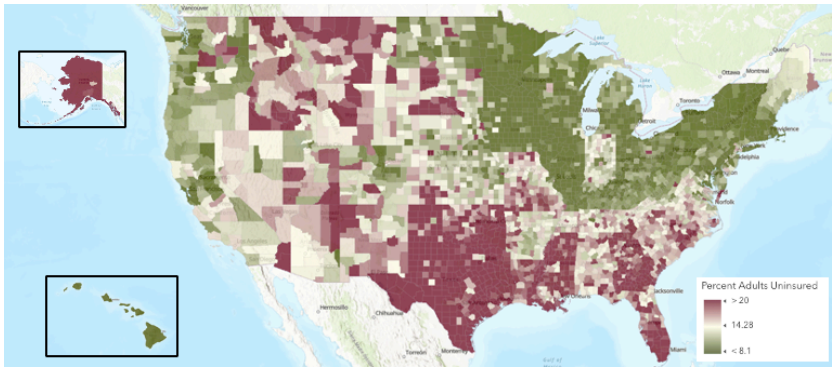
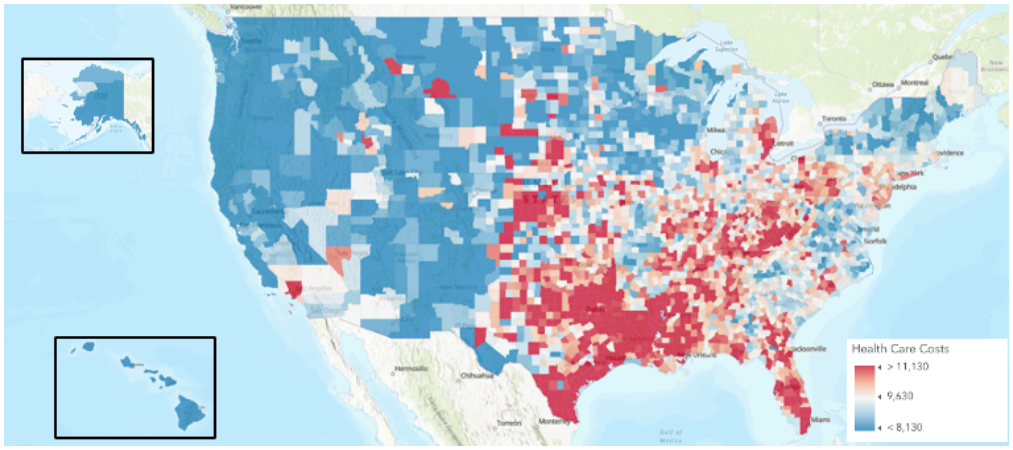


Figure 40 shows the geospatial distribution of the household average annual healthcare costs above and below the mean ($9,630) in the United States. Red shades point to areas of higher age-adjusted mortality rates than the national mean (i.e., central, southern, and southeastern United States).

Figure 40

The US 2018 Geospatial Distribution of Household Average Annual Health Care Costs



Education and Income. The education attainment variables for HS graduation rate in a 4-year cohort showed a county mean graduation rate of 73.3%. The county mean for 25–44-year-olds with some college (incomplete postsecondary education) without a degree attained was 57.2%. The income-related variables of showed a mean of $20,898 for people living under the 20th percentile of income, $49,506 for MHI, and a mean income ratio (80th/20th percentile) (inequality) of 4.5 (see Table 8 and Figures 41- 45). Table 8 shows the descriptive statistics for the educational attainment and income related SDoH variables.

Table 8

Descriptive statistics of Education and Income-related SDoH.

Education & Income Related SDoH Descriptive Statistics

		Percent of Cohort Graduating from High School	Percen Population 25-44 with Some College	Population Percent at 20th Percentile Income	Median Household Income	Income Ratio /Income Inequality
N	Valid	3142	3142	3142	3142	3142
	Missing	0	0	0	0	0
Mean		73.3014	57.2305	20897.95	49506.35	4.520
Std. Error of Mean		.56497	.20606	111.152	230.414	.0133
Median		86.0000	57.0650	20198.00	47586.50	4.400
Mode		.00	64.63	21563	41128[a]	4.5
Std. Deviation		31.66884	11.55042	6230.447	12915.510	.7442
Variance		1002.915	133.412	38818473.754	166810408.161	.554
Skewness		-1.753	-.073	1.143	1.367	1.005
Std. Error of Skewness		.044	.044	.044	.044	.044
Kurtosis		1.374	-.246	2.937	3.595	3.322
Std. Error of Kurtosis		.087	.087	.087	.087	.087
Range		100.00	78.54	60890	134609	8.9
Minimum		.00	15.51	0	0	.0
Maximum		100.00	94.05	60890	134609	8.9

[a] Multiple modes exist. The smallest value is shown

Figure 41 shows the geospatial distribution of HS graduation rate, in a 4-year cohort, above and below the mean (86.1%) in the United States. Red shades point to areas of lower HS graduation rates than the national mean (i.e., northwestern, western, southeastern, and eastern United States).

Figure 41

The US 2018 Geospatial Distribution of HS Graduation Percent (Four-Year Cohort)

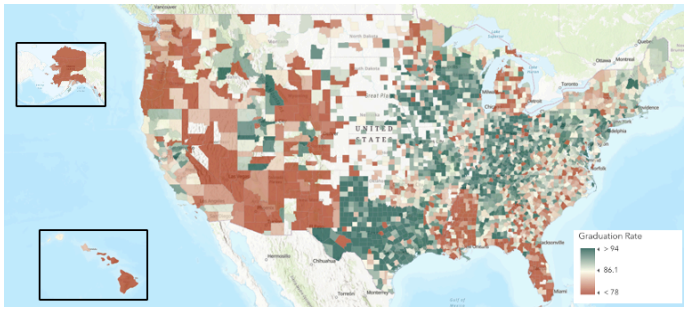


Figure 42 shows the geospatial distribution of the population percent of adults 25-44) with some (incomplete) college above and below the mean (57.2%) in the United States. Red shades point to areas with lower educational attainment than the national mean (i.e., western, central, southern, and southeastern United States).

Figure 42

The US 2018 Geospatial Distribution of Percent Adults 25-44) With Some College

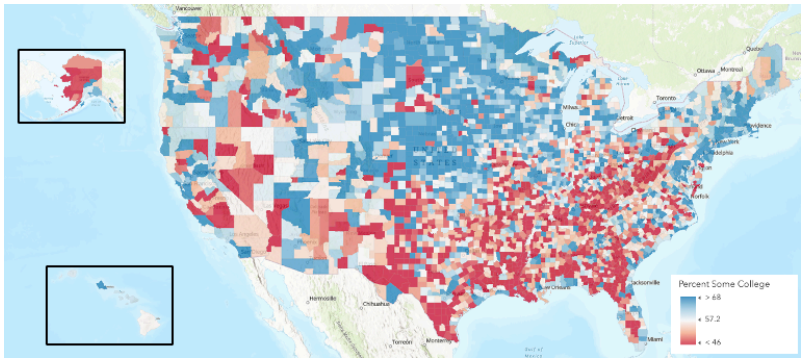


Figure 43 shows the geospatial distribution of the population under the 20th percentile of income above and below the mean ($20,911) in the United States. Red shades point to areas where people earn less than the mean 20th percentile than the national mean (i.e., western, central, southern, and southeastern United States).

Figure 43

The US 2018 Geospatial Distribution of Population Under the 20th Percentile of Income

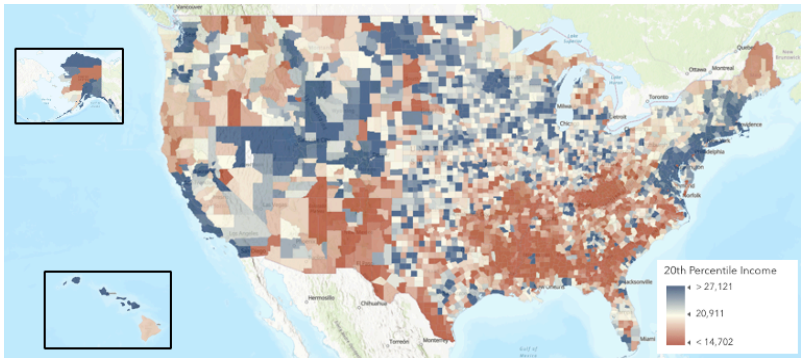


Figure 44 shows the geospatial distribution of the population of MHI above and below the mean ($49,522) in the United States. Burgundy shades point to areas of households earning less than the national mean of MHI (i.e., northwestern, western, northcentral, central, southern, and southeastern United States).

Figure 44

The US 2018 Geospatial Distribution of Median Household Income

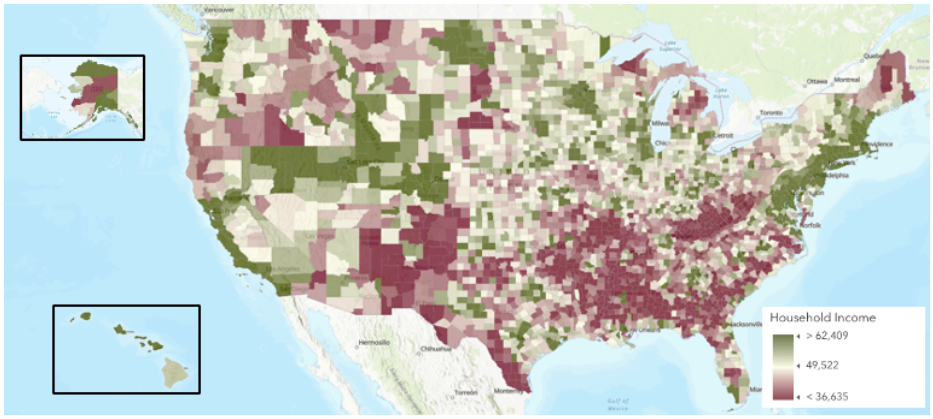
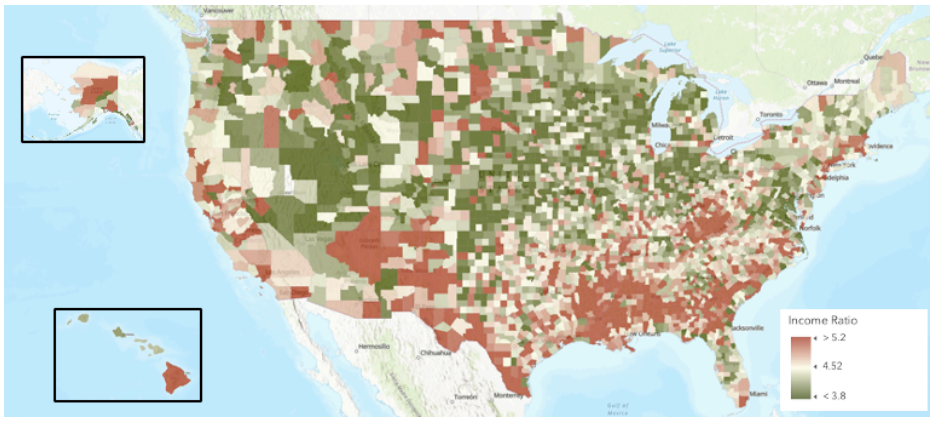


Figure 45 shows the geospatial distribution of Income Inequality above and below the mean (4.5) in the United States. Bright-brown shades point to areas of higher income inequality (i.e., northwestern, western, northcentral, central, southern, and southeastern United States).

Figure 45

The US 2018 Geospatial Distribution of Income Ratio of Income Inequality



Environment and Pollution. The descriptive statistics of environment and pollution-related variables showed a mean average daily particulate matter concentration PM 2.5 of 8.9 a mean rural population percentage of 58.5%, a mean rank of 46.8/242 for both, county health rank and county health outcomes rank (see Table 9 and Figures 46 - 49).

Table 9

Descriptive statistics of Environment and Pollution-related SDoH.

Environment & Pollution Related SDoH Descriptive Statistics

		Air_Pollution_PM25	Population Percent Rural	County Health Behaviors Rank	County Health Outcomes Rank
N	Valid	3142	3142	3142	3142
	Missing	0	0	0	0
Mean		8.855	58.4515	46.76	46.76
Std. Error of Mean		.0326	.56318	.744	.744
Median		9.200	59.3950	37.00	37.00
Mode		9.3	100.00	0	0
Std. Deviation		1.8269	31.56833	41.715	41.715
Variance		3.338	996.560	1740.119	1740.119
Skewness		-1.364	-.157	1.713	1.713
Std. Error of Skewness		.044	.044	.044	.044
Kurtosis		4.661	-1.141	3.919	3.919
Std. Error of Kurtosis		.087	.087	.087	.087
Range		15.4	100.00	242	242
Minimum		.0	.00	0	0
Maximum		15.4	100.00	242	242

Figure 46 shows the geospatial distribution of the average daily particulate matter PM 2.5 (air pollution) above and below the mean (8.95 μg/m3) in the United StatesUS. Red shades point to areas of higher pollution (i.e., southwestern, northcentral, central, southern, and southeastern United States).

Figure 46

The US 2018 Geospatial Distribution of Average Daily PM 2.5 (Air Pollution)

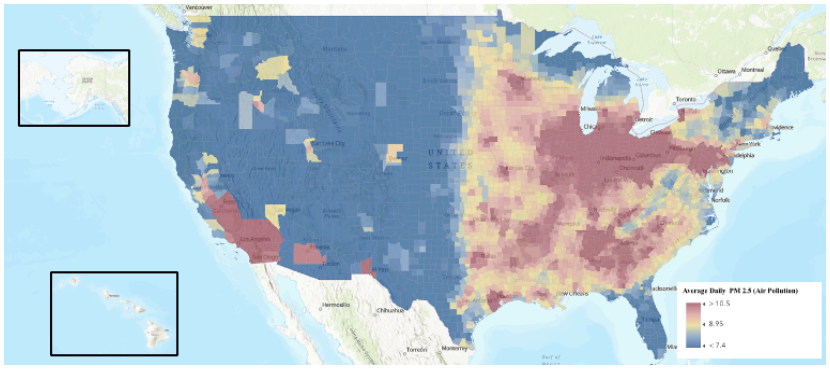


Figure 47 shows the geospatial distribution of rural population above and below the mean (58.5%) in the United States. Purple shades point to areas of higher rural population percent (i.e., northcentral, central, southern, southeastern, and northeastern United States).

Figure 47

The US 2018 Geospatial Distribution Of Rural Population Percent

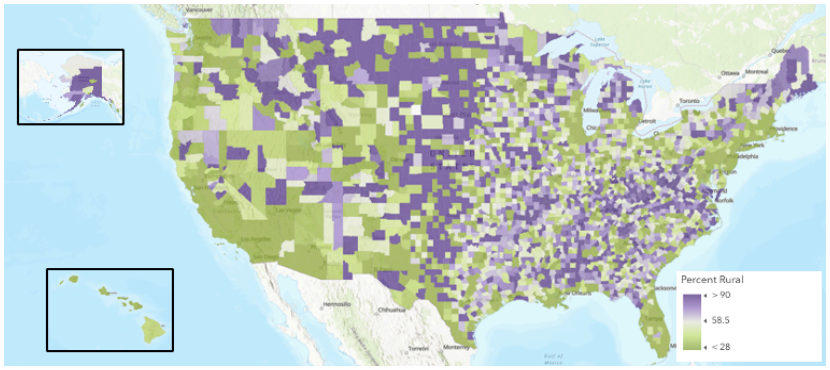


Figure 48 shows the geospatial distribution of U.S. Counties' Health Behaviors Ranks above and below the mean (47.7). Red shades point to areas of worse health behavior ranks (i.e., northcentral, central, southern, southeastern, and northeastern United States).

Figure 48

The US 2018 Geospatial Distribution of US Counties' Health Behaviors Ranks

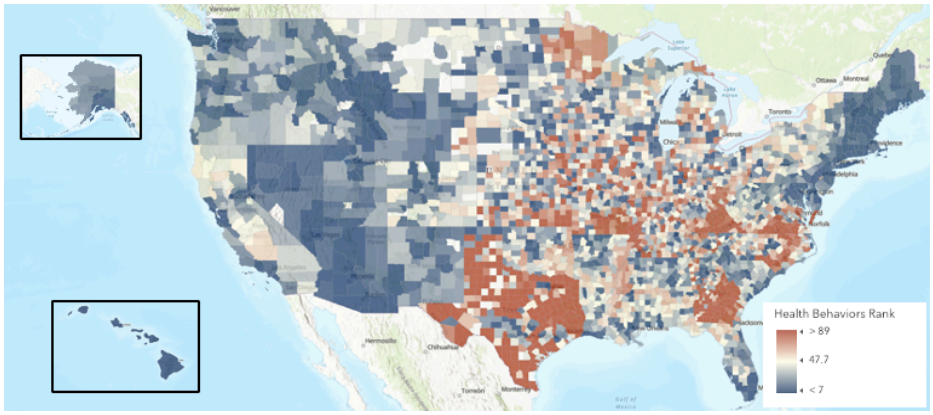
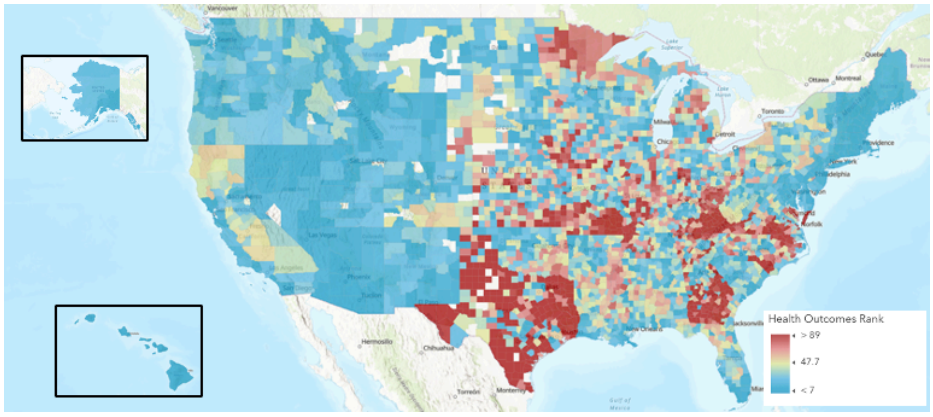


Figure 49 shows the geospatial distribution of U.S. Counties' Health Outcomes Ranks above and below the mean (47.7). Red shades point to areas of worse health outcomes ranks (i.e., northcentral, central, southern, southeastern, and northeastern United States).

Figure 49

The US 2018 Geospatial Distribution of US Counties' Health Outcomes Ranks



Alzheimer's Disease and Related Dementias (Outcome Variable). The outcome variable ADRD prevalence showed a normally distributed, slightly negatively skewed, and kurtotic distribution, with a sample mean ~$\bar{x}_{\underline{G}}$ = 10.0 %, standard deviation ~s_G = 2.6%, and a median ~$\tilde{x}_{\underline{G}}$ = 10.1%, a minimum of 0, and a maximum of 30% for the general population. The Population under 65, had a sample mean ~$\bar{x}_U$ = 3.0 %, standard deviation s_U = 2.3%, and a median $\tilde{x}_U$ = 3.4%, a minimum of 0, and a maximum of 19.8% with a slightly positively skewed and platykurtic distribution. The population older than 65, showed a sample mean $\bar{x}_O$ = 8.61 %, standard deviation s_O = 5.5%, and a median $\tilde{x}_O$ = 10.7%, a minimum of 0, and a maximum of 32% with a slightly negatively skewed and platykurtic distribution for n = 3,142 counties (see Table 10 and Figures 50–55).

Table 10

The descriptive statistics for ADRD for N= 3,142 Counties in the US for 2018.

Statistics for ADRD

		ADRD Prevalence Total Population	ADRD Prevalence Population <65	ADRD Prevalence Population >65
N	Valid	3142	3142	3142
	Missing	0	0	0
Mean		9.965120	3.0397	8.6082
Std. Error of Mean		.0462925	.04073	.09893
Median		10.107550	3.4300	10.7000
Mode		.0000	.00	.00
Std. Deviation		2.5948589	2.28294	5.54520
Variance		6.733	5.212	30.749
Skewness		-.712	.244	-.591
Std. Error of Skewness		.044	.044	.044
Kurtosis		6.320	.807	-.771
Std. Error of Kurtosis		.087	.087	.087
Range		30.0327	19.80	32.00
Minimum		.0000	.00	.00
Maximum		30.0327	19.80	32.00

Figure 50 shows the normal distribution of ADRD prevalence in the 2018 general population with a mean of approximately 10% (9.97%) in the US converges with Table 10 and Figure 51.

Figure 50

The US 2018 Distribution of ADRD Prevalence in the General Population

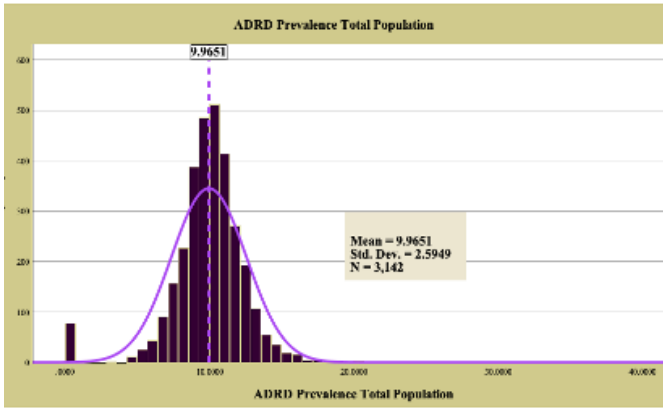


Figure 51 shows the geospatial distribution of ADRD prevalence in the 2018 general population above and below the mean (9.96%) for the 2018 General Population in the US converges with Figure 50 and Table 10.

Figure 51

The US 2018 Distribution of ADRD Prevalence in the General Population

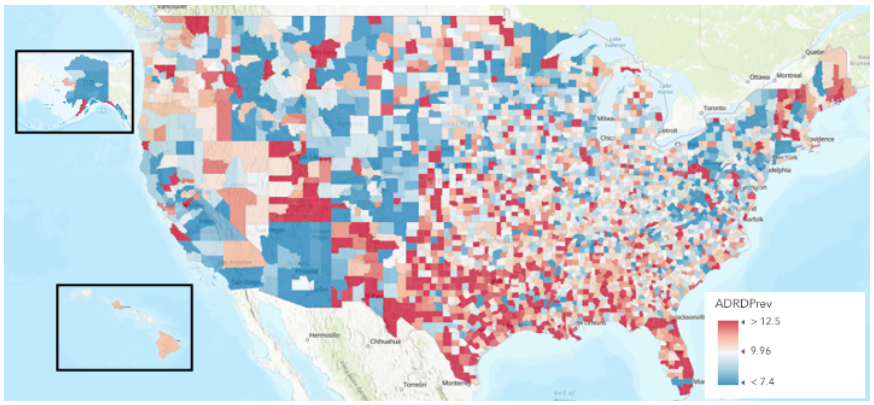


Figure 51 showed higher ADRD prevalence among the general population, depicted by a darker red shade, was observed in the North-Northeastern, Midwestern, Southern, and Southeastern regions of the United States, Alaska, and Hawaii. This correlates with the ethnographic distribution in those areas and their related higher ADRD prevalence among non-Hispanic Black, American Indians, Alaskan Natives, Hawaiians, and Latinos.

Figure 52 shows the normal distribution of ADRD prevalence in the 2018 population <65 with a mean of approximately 3% in the US correlates to Table 10 and Figure 53.

Figure 52

The US 2018 Distribution of ADRD Prevalence for Population Under 65.

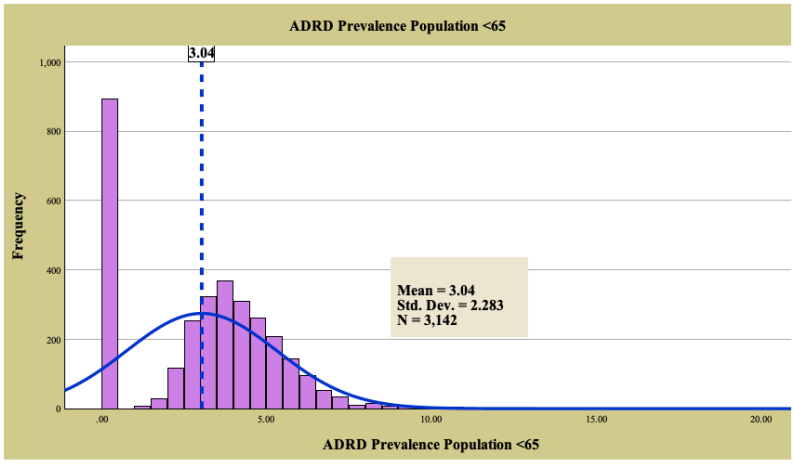
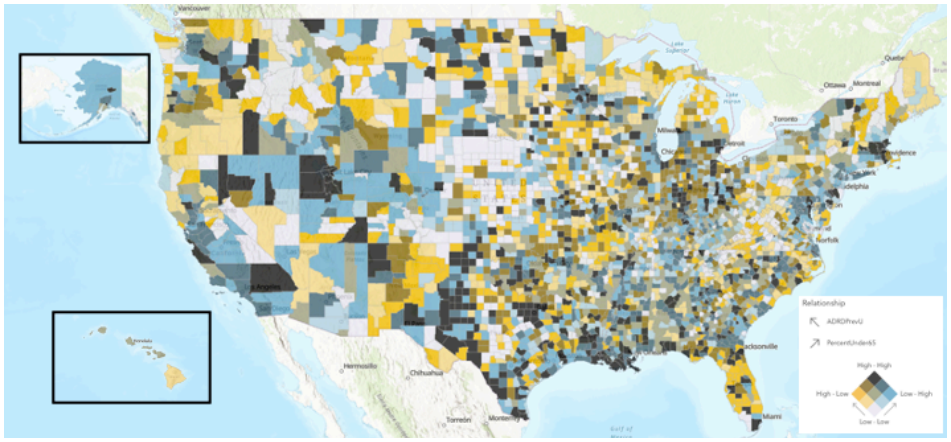


Figure 53 shows the geospatial distribution of the outcome variable ADRD prevalence for the 2018 Population <65 in the US converging with Figure 52 and Table 10.

Figure 53

The US 2018 Geospatial distribution of ADRD prevalence for Population Under 65



Higher ADRD prevalence converging with high population percentage under 65 (black shade) was observed in the same Northern, Midwestern, Southern, and Southeastern regions of the United States, Alaska, and in lesser amounts in Hawaii. This distribution correlates with the ethnographic composition and related higher ADRD prevalence in those areas. Hawaii and the northeast showed higher ADRD with a low percentage of the population under 65.

Figure 54 shows the normal distribution of ADRD prevalence in the 2018 population >65 with a mean of approximately 8.6% in the US correlating to Table 10 and Figure 55.

Figure 54

The US 2018 Distribution of ADRD Prevalence for the Population Over 65

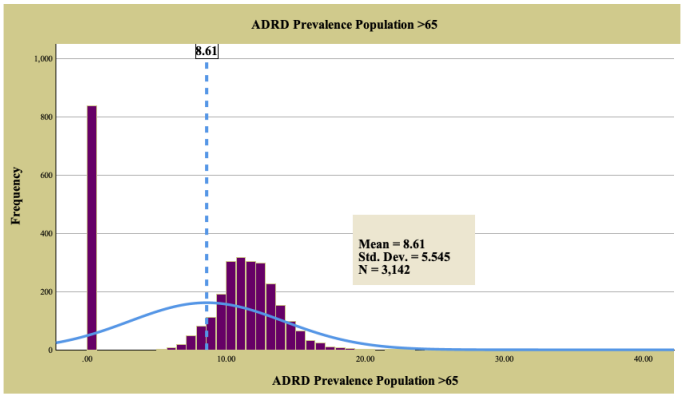


Figure 55

The US 2018 Geographic Distribution of ADRD Prevalence for the Population Over 65

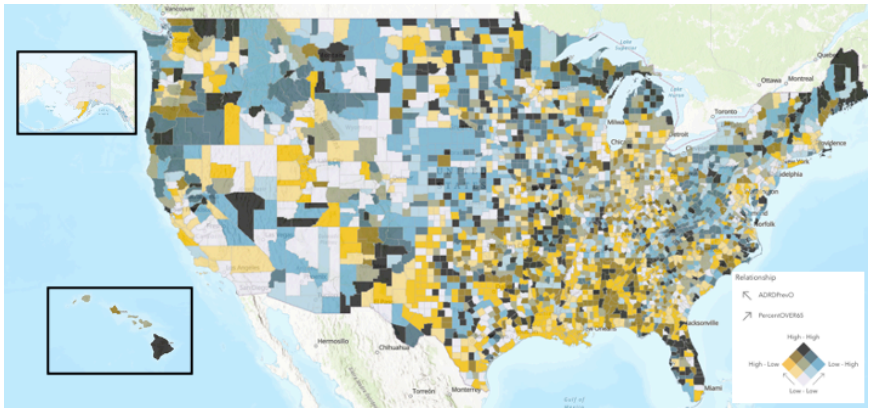


Figure 55 shows a higher prevalence of ADRD converging with a high percentage of individuals over 65 (black shade) observed in the North–Northeastern, Midwestern, Southern, and Southeastern regions of the United States, and Hawaii. This distribution correlates with the ethnographic composition and related higher ADRD prevalence in those areas. Alaska showed low ADRD with a low percentage of the population under 65.

Type 2 Diabetes Mellitus (Moderator Variable). The comorbidity and modifier variable T2DM prevalence showed a normally distributed, slightly negatively skewed, and leptokurtotic (kurtosis > 3) distribution, with a sample mean $\bar{x}_{\underline{G}}$ = 26.36 %, standard deviation s_G = 6.15%, and a median $\tilde{x}_{\underline{G}}$ = 26.90%, a minimum of 0, and a maximum of 50.24% for the general population. The Population under 65, had a sample mean $\bar{x}_U$ = 24.81 %, standard deviation s_U = 8.245%, and a median $\tilde{x}_U$ = 26.2%, a minimum of 0, and a maximum of 56.7% with a slightly negatively skewed and slightly leptokurtic distribution. The population older than 65, showed a sample mean $\bar{x}_O$ = 25.50 %, standard deviation s_O = 8.384%, and a median $\tilde{x}_O$ = 26.9%, a minimum of 0, and a maximum of 32% with a slightly negatively skewed and slightly leptokurtic distribution for n = 3,142 counties (see Table 11 and Figures 56–61)

Table 11 shows the descriptive statistics of T2DM for the general population and for the populations over and under 65 years of age.

Table 11

The Descriptive Statistics for T2DM for n= 3,142 US Counties in 2018.

Statistics

		T2DM Prevalence Total Population	T2DM Prevalence Population <65	T2DM Prevalence Population >65
N	Valid	3142	3142	3142
	Missing	0	0	0
Mean		26.359283	24.8078	25.5013
Std. Error of Mean		.1097085	.14709	.14958
Median		26.899000	26.2000	26.9000
Mode		.0000	.00	.00
Std. Deviation		6.1495521	8.24493	8.38433
Variance		37.817	67.979	70.297
Skewness		-1.319	-1.523	-1.617
Std. Error of Skewness		.044	.044	.044
Kurtosis		5.088	3.345	3.289
Std. Error of Kurtosis		.087	.087	.087
Range		50.2415	56.70	48.60
Minimum		.0000	.00	.00
Maximum		50.2415	56.70	48.60

Figure 56 shows the normal distribution of T2DM prevalence in the 2018 general population with a mean of approximately 26.4% in the US correlating to Table 11 and Figure 57.

Figure 56

The Distribution of T2DM in the General Population for n= 3,142 US Counties in 2018.

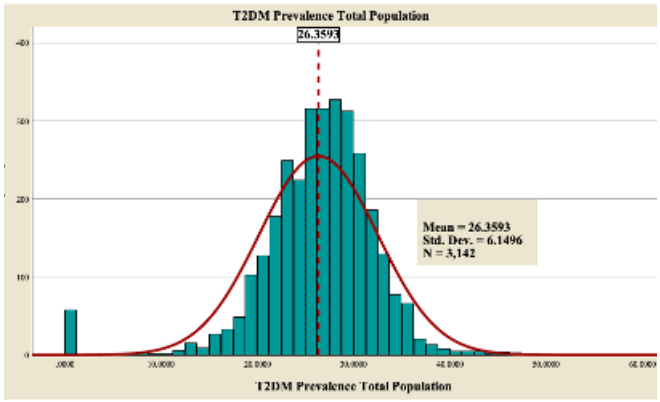
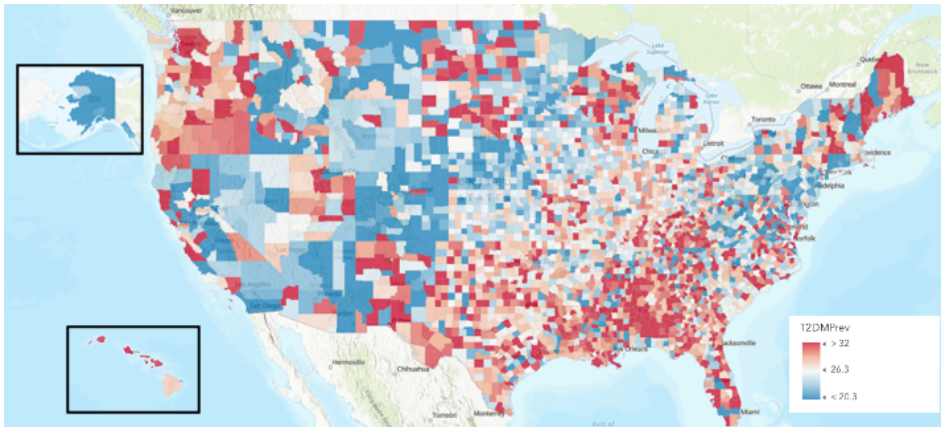


Figure 57 shows the geospatial distribution of the comorbidity and modifier variable T2DM prevalence above and below the mean (26.4%) for the 2018 General Population in the US converges with Figure 56 and Table 11.

Figure 57

The US 2018 Geospatial Distribution of T2DM prevalence in the General Population



Higher T2DM prevalence among the general population, (darker red shade), was observed in the North-Northeastern, Midwestern, Southern, and Southeastern regions of the United States, and Hawaii. This geospatial distribution correlated to the ADRD prevalence distribution (Figure 56), and the historic ethnographic composition and related higher ADRD prevalence in those areas among non-Hispanic Black, AIAN, Hawaiians, and Latinos. Figure 58 shows the normal distribution of T2DM prevalence in the 2018 population <65 with a mean of approximately 24.8%.

Figure 58 shows the distribution of the comorbidity and modifier variable T2DM prevalence for the 2018 Population Under 65 in the US converges with Table 11 and Figure 59.

Figure 58

The Distribution of T2DM in the Population Under 65 for n= 3,142 US Counties in 2018

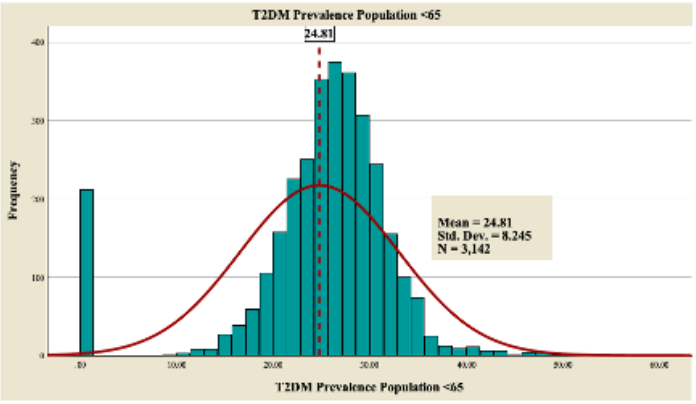
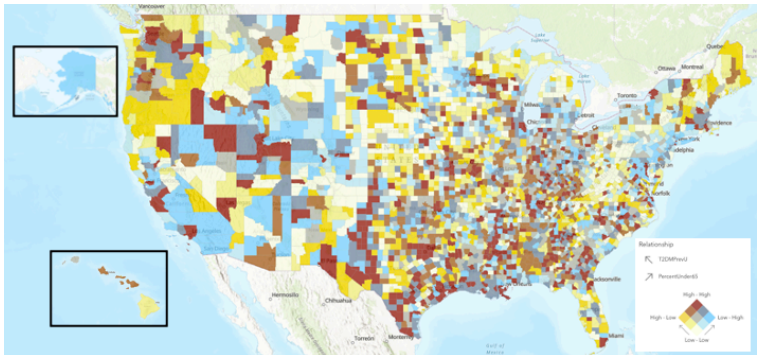


Figure 59 shows the geospatial distribution of the comorbidity and modifier variable T2DM prevalence for the 2018 <65 Population in the US converges with Figure 58 and Table 11.

Figure 59

The US 2018 Geospatial Distribution of T2DM prevalence in the Population Under 65 .



Higher T2DM prevalence with a higher percentage of the population under 65, (bright brown shade) was observed in the Northern, Midwestern, Southern, and Southeastern regions of the United States, and Hawaii. This geospatial distribution correlated to the ADRD prevalence distribution (Figure 58), and the historically ethnographic composition related higher ADRD prevalence in those areas among non-Hispanic Black, AIAN, Hawaiians, and Latinos. Figure 60 shows the normal distribution of ADRD prevalence in the 2018 population >65 with a mean of approximately 25.5%.

Figure 60 shows the distribution of the comorbidity and modifier variable T2DM prevalence for the 2018 Population Over 65 in the US converges with Table 11 and Figure 61.

Figure 60

The Distribution of T2DM in the Population Over 65 for n= 3,142 US Counties in 2018

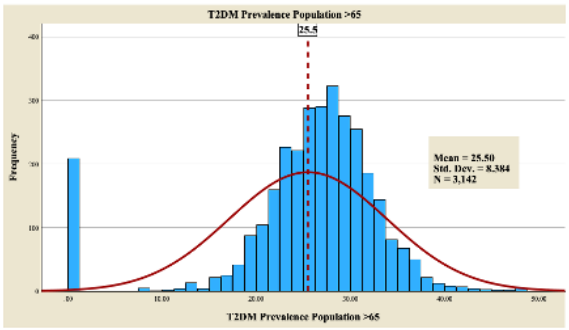
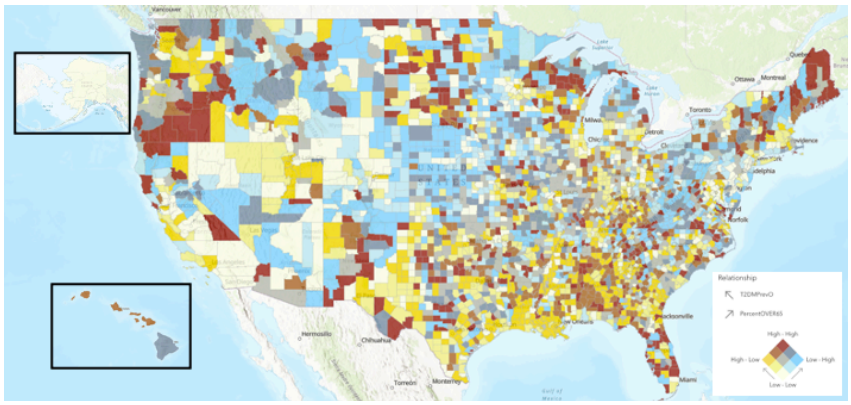


Figure 61 shows *the geospatial distribution of the comorbidity and modifier variable T2DM prevalence for the 2018 >65 Population in the US converges with Figure 60 and Table 4.*

Figure 61

The US 2018 Geospatial Distribution of T2DM prevalence for the Population Over 65



Higher T2DM prevalence with a higher percentage of the population over 65 (bright brown shade) was observed in the Northern, Northeastern, Midwestern, Southern, and Southeastern regions of the United States, and Hawaii. This geospatial distribution correlated to the ADRD prevalence distribution, and the historically ethnographic

composition related to higher ADRD prevalence in those areas. Alaska showed lower T2DM prevalence and a lower population >65 percent.

Hypertension (Covariate). The comorbidity and covariate AH prevalence revealed a mean of 55.83% for the general population, 40.86% for the population <65, and 57.06% for the population > 65 (see Table 12). Table 12 shows the descriptive statistics for the covariate AH for the U.S. 2018 general population, population under and over 65 years of age.

Table 12

The Descriptive Statistics for Hypertension n= 3,142 US Counties in the US 2018

Statistics

		Hypertension Prevalence Total Population	Hypertension Prevalence Population <65	Hypertension Prevalence Population >65
N	Valid	3142	3142	3142
	Missing	0	0	0
Mean		55.827127	40.863915	57.057662
Std. Error of Mean		.2049040	.2300721	.2786873
Median		58.602900	43.023800	61.352000
Mode		.0000	.0000	.0000
Std. Deviation		11.4855967	12.8963573	15.6214096
Variance		131.919	166.316	244.028
Skewness		-2.283	-1.384	-2.371
Std. Error of Skewness		.044	.044	.044
Kurtosis		8.214	2.669	6.139
Std. Error of Kurtosis		.087	.087	.087
Range		75.7522	70.7006	78.8708
Minimum		.0000	.0000	.0000
Maximum		75.7522	70.7006	78.8708

Figure 62 shows the normal distribution of hypertension prevalence in the 2018 general population with a mean of approximately 55.8% in the general population converges with Table 12 and Figure 63.

Figure 62

The Distribution of Hypertension Prevalence in the General Population in 2018

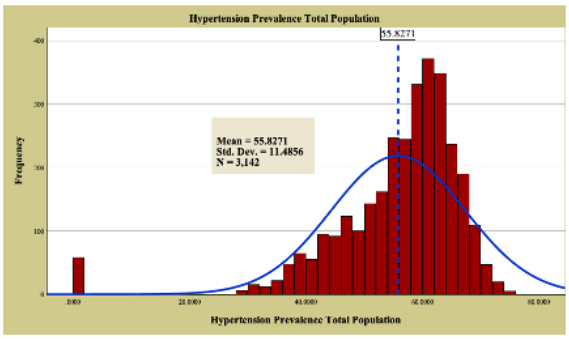


Figure 63 shows the geospatial distribution of AH prevalence for the 2018 U.S. general population above and below the mean (55.8%). Red shades point to areas with higher AH prevalence as observed in the Northern, Midwestern, Southern, and Southeastern regions of the United States, and Hawaii. This geospatial distribution correlated to the AH prevalence distribution, and the historically ethnographic composition related to higher AH prevalence in those areas. Alaska showed lower AH prevalence and a lower population >65 percent.

Figure 63

The US 2018 Geospatial Distribution of Hypertension Prevalence for the General Population

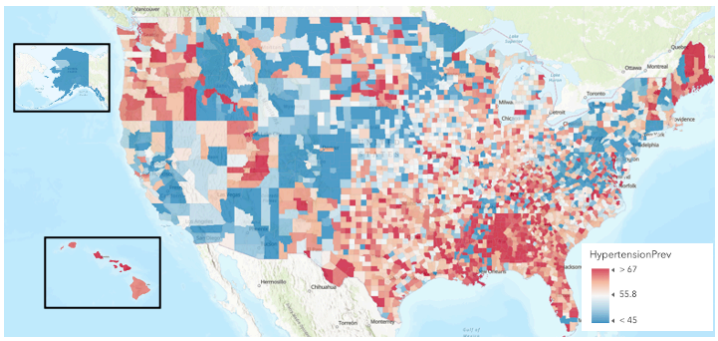


Figure 64 shows the normal distribution of hypertension prevalence in the 2018 population <65 with a mean of approximately 40.9% converges with Table 12 and Figure 65..

Figure 64

The US 2018 Distribution of Hypertension Prevalence in the Population Under 65

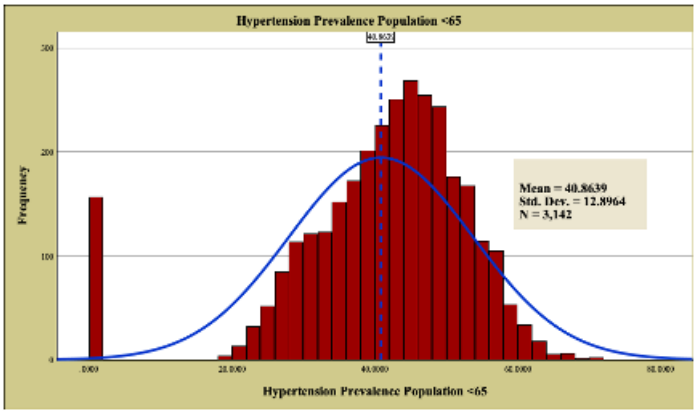


Figure 65 shows te geospatial distribution of AH prevalence for the 2018 U.S. population <65 above and below the mean (40.9%) converges with Table 12 and Figure 64.. Purple shades point to areas with higher AH prevalence as observed in the Northern, Midwestern, Southern, Southeastern, and Northeastern regions of the United States, and Hawaii. This geospatial distribution correlated to the AH prevalence distribution, and the historically ethnographic composition related to higher AH prevalence in those areas. Alaska showed lower AH prevalence in the population <65 percent.

Figure 65

The US 2018 Geospatial Distribution of Hypertension Prevalence in the Population Under 65

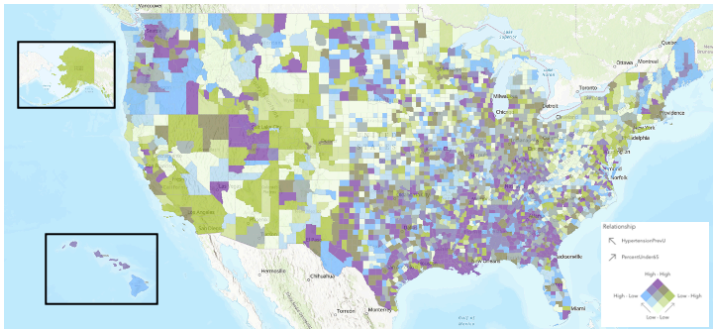


Figure 66 shows the normal distribution of hypertension prevalence in the 2018 population >65 with a mean of approximately 57.0% *converges with Table 12 and Figure 67.*

Figure 66

The US 2018 Distribution of Hypertension Prevalence in the Population Over 65

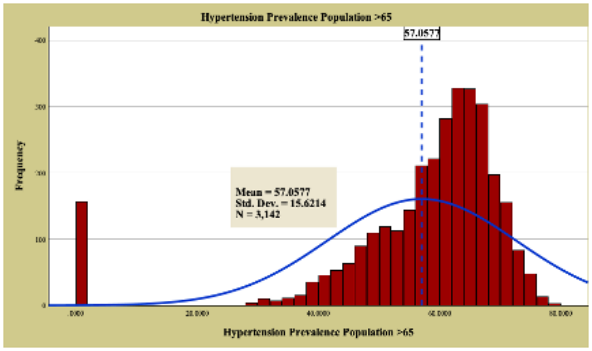
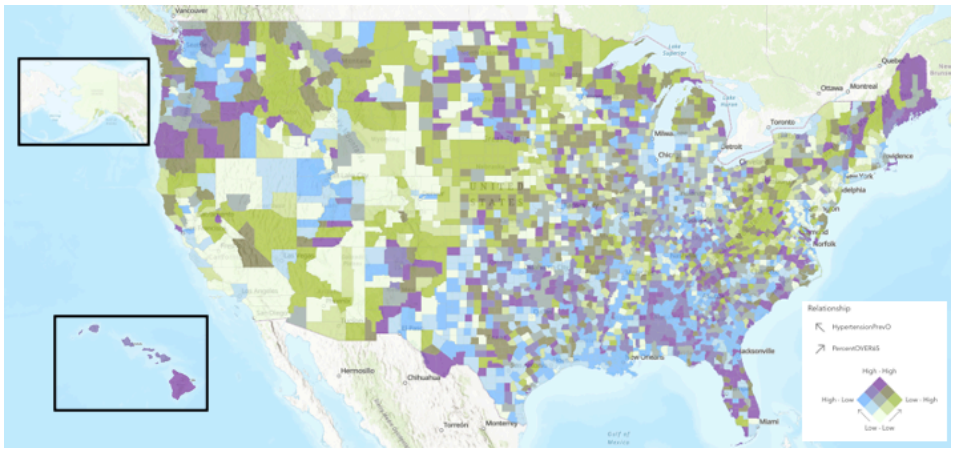


Figure 67 shows te geospatial distribution of AH prevalence for the 2018 U.S. population >65 above and below the mean (57.0%) converges with Table 12 and Figure 66. Purple shades point to areas with higher AH prevalence as observed in the Northern, Midwestern, Southern, Southeastern, and Northeastern regions of the United States, and

Hawaii. This geospatial distribution correlated to the AH prevalence distribution, and the historically ethnographic composition related to higher AH prevalence in those areas. Alaska showed lower AH prevalence and a lower population >65 percent.

Figure 67

The US 2018 Geospatial Distribution of Hypertension Prevalence in the Population > 65



Osteoporosis (Covariate). The comorbidity and covariate OP prevalence showed a mean of 5.37% for the general population, 1.397% for the population <65, and 3.93% for the population > 65 (see Table 13). Table 13 shows the descriptive statistics for the covariate OP for the U.S. 2018 general population, population under and over 65 years of age.

Table 13

The Descriptive Statistics of Osteoporosis Prevalence for n= 3,142 US Counties in 2018

Statistics

		Osteoporosis Prevalence Total Population	Osteoporosis Prevalence Population <65	Osteoporosis Prevalence Population >65
N	Valid	3142	3142	3142
	Missing	0	0	0
Mean		5.371179	1.3969	3.9335
Std. Error of Mean		.0343804	.02470	.06197
Median		5.369150	1.5950	5.0300
Mode		.0000	.00	.00
Std. Deviation		1.9271449	1.38472	3.47369
Variance		3.714	1.917	12.067
Skewness		-.126	.604	.009
Std. Error of Skewness		.044	.044	.044
Kurtosis		2.010	.676	-1.472
Std. Error of Kurtosis		.087	.087	.087
Range		16.9545	10.60	15.70
Minimum		.0000	.00	.00
Maximum		16.9545	10.60	15.70

Figure 68 shows the normal distribution of hypertension prevalence in the 2018 U.S. general population with a mean of approximately 5.4% converges with Table 32 and Figure 69.

Figure 68

The US 2018 Distribution of Osteoporosis Prevalence in the General Population

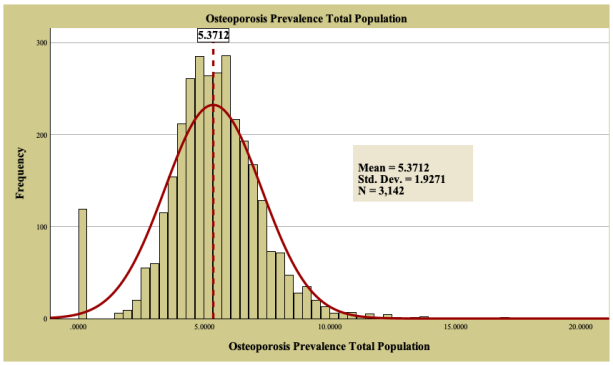


Figure 69 shows the geospatial distribution of OP prevalence for the 2018 U.S. general population above and below the mean (5.4%) converges with Table 13. Red shades point to areas with higher OP prevalence as observed throughout the United

States, including Hawaii. This geospatial distribution correlated to the OP prevalence distribution, and the historically ethnographic composition related to higher OP prevalence in those areas. Alaska showed lower OP prevalence and a lower population >65 percent.

Figure 69

The US 2018 Geospatial Distribution of Osteoporosis Prevalence in the General Population

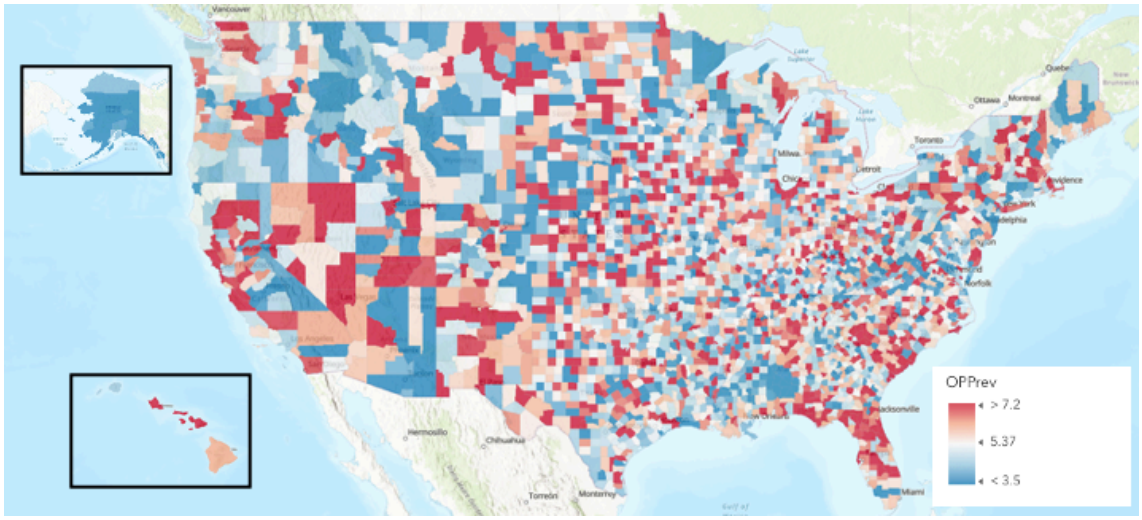


Figure 70 shows the normal distribution of OP prevalence in the 2018 U.S. population <65 with a mean of approximately 1.4% converging with Table 13 and Figure 71.

Figure 70

The US 2018 Distribution of Osteoporosis Prevalence in the Population Under 65

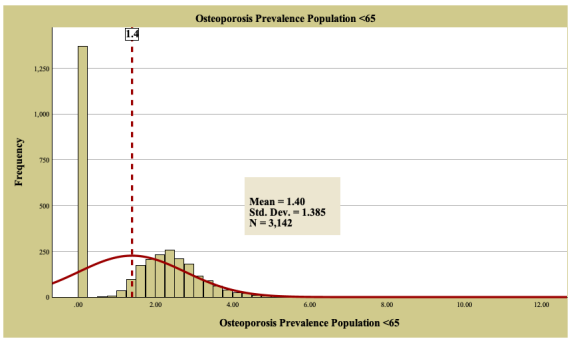


Figure 71 shows the geospatial distribution of OP prevalence for the 2018 U.S. population <65 above and below the mean (1.4%) converges with Table 13 and Figure 70. Bright-brown shades point to areas with higher OP prevalence as observed throughout the continental United States, including Hawaii. This geospatial distribution correlated to the OP prevalence distribution, and the historically ethnographic composition related to higher OP prevalence in those areas. Alaska showed lower OP prevalence in the population <65.

Figure 71

The US 2018 Geospatial Distribution of Osteoporosis Prevalence for the Population <65

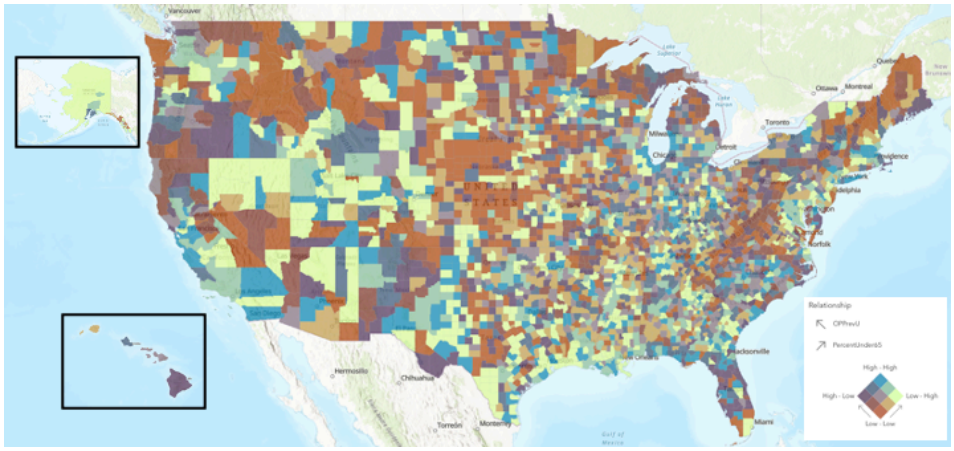


Figure 72 shows the normal distribution of OP prevalence in the 2018 U.S. population <65 with a mean of approximately 3.9% converging with Table 13 and Figure 73.

Figure 72

The US 2018 Distribution of Osteoporosis Prevalence Population >65

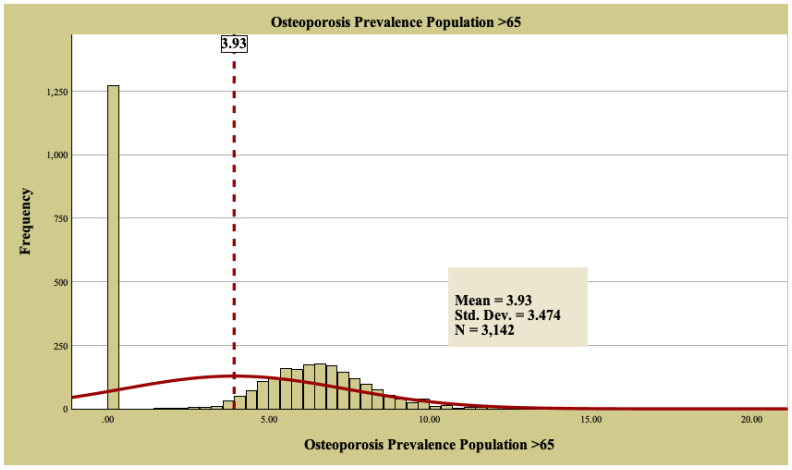
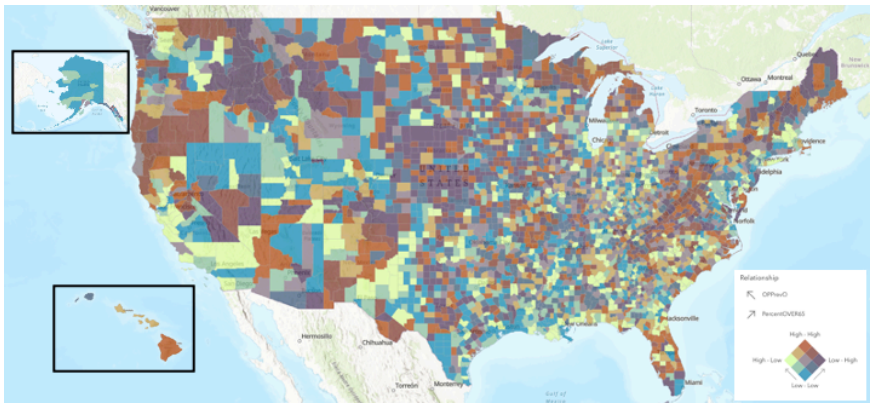


Figure 73 shows te geospatial distribution of OP prevalence for the 2018 U.S. population >65 above and below the mean (3.9%) converges with Table 13 and Figure 72. Bright-brown shades point to areas with higher OP prevalence as observed throughout the continental United States, including Hawaii. This geospatial distribution correlated to the OP prevalence distribution, and the historically ethnographic composition related to higher OP prevalence in those areas. Alaska showed lower OP prevalence and lower population percentage under 65.

Figure 73

The US 2018 Geospatial Distribution of Osteoporosis in the Population Over 65



Schizophrenia and Other Psychotic Disorders (Covariate). The comorbidity and covariate SZ and other psychotic disorders prevalence showed a mean of 2.4 % for the general population, 6.8% for the population <65, and 1.3% for the population > 65 for N= 3,142 counties in the US for 2018 (see Table 14 and Figures 74–78).

Table 14

The Descriptive Statistics of Schizophrenia and Other Psychotic Disorders Prevalence

Statistics

		Schizophrenia & Other Psychotic Disorders Prevalence Total Population	Schizophrenia & Other Psychotic Disorders Prevalence Population <65	Schizophrenia & Other Psychotic Disorders Prevalence Population >65
N	Valid	3142	3142	3142
	Missing	0	0	0
Mean		2.4210	6.8308	1.2955
Std. Error of Mean		.02304	.07943	.01671
Median		2.4000	7.2200	1.3100
Mode		.00	.00	.00
Std. Deviation		1.29140	4.45230	.93668
Variance		1.668	19.823	.877
Skewness		.885	.206	1.004
Std. Error of Skewness		.044	.044	.044
Kurtosis		7.448	.812	6.750
Std. Error of Kurtosis		.087	.087	.087
Range		17.60	33.80	12.30
Minimum		.00	.00	.00
Maximum		17.60	33.80	12.30

Figure 74 shows *the normal distribution of the Schizophrenia (SZ) and other psychotic disorders prevalence variable in the 2018 US population>65 converging with Table 13 and Figure 75.*

Figure 74

The US 2018 Distribution of Schizophrenia and Other Psychotic Disorders Prevalence Population Over 65

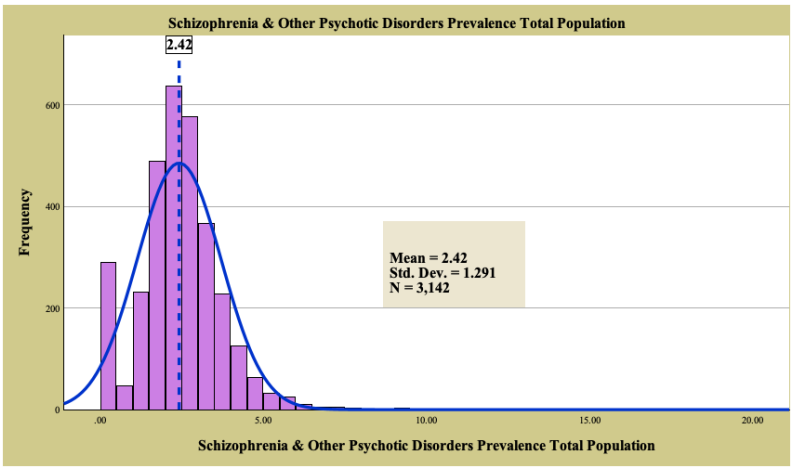


Figure 75 shows the geospatial distribution of SZ and other psychotic disorders prevalence for the 2018 U.S. general population above and below the mean (2.4%) converges with Table 14. Red shades point to areas with higher SZ prevalence as observed throughout the continental United States, including Hawaii and Alaska.

Figure 75

The US 2018 Geospatial Distribution of Schizophrenia and Other Psychotic Disorders Prevalence in the General Population

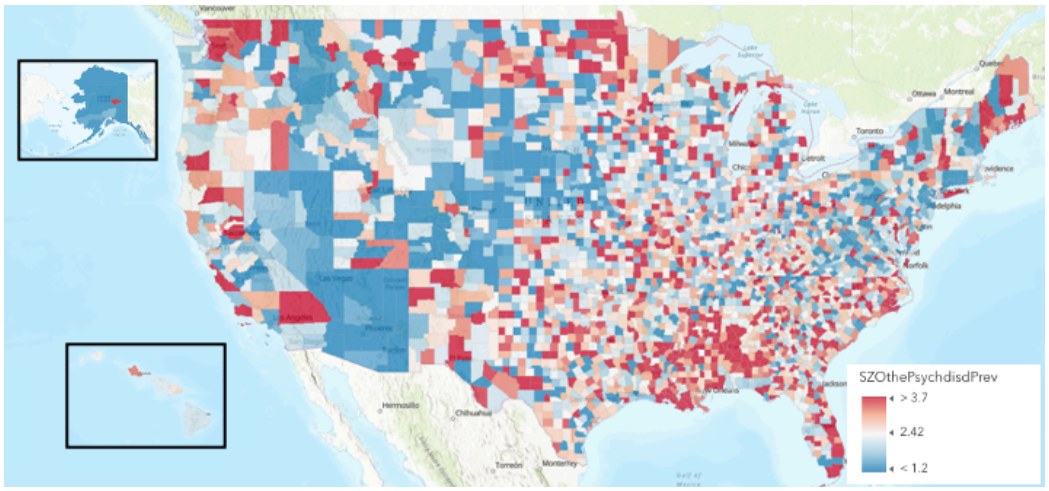


Figure 76 shows the normal distribution of SZ prevalence in the 2018 U.S. population <65 with a mean of approximately 6.8% converging with Table 14 and Figure 77.

Figure 76

The US 2018 Distribution of Schizophrenia and Other Psychotic Disorders Prevalence in the Population Under 65

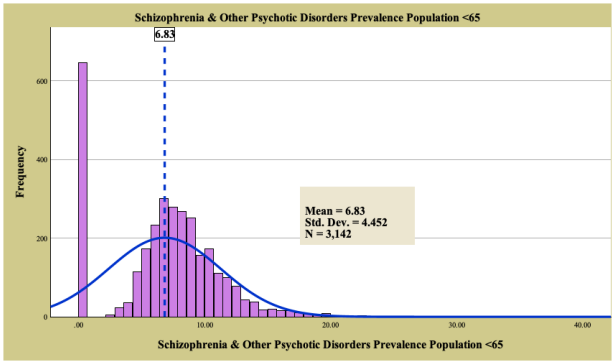


Figure 77 shows te geospatial distribution of SZ and other psychotic disorders prevalence for the 2018 U.S. population <65 above and below the mean (6.8%) converges with Table 14 and Figure 76. Orange shades point to areas with higher SZ prevalence as observed throughout the continental United States, including Hawaii and Alaska.

Figure 77

The US 2018 Geospatial Distribution of Schizophrenia and Other Psychotic Disorders Prevalence in the Population Under 65

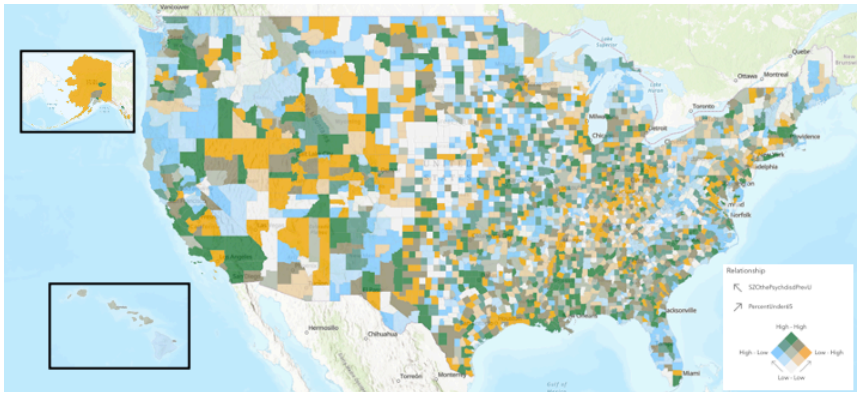


Figure 78 shows the normal distribution of SZ prevalence in the 2018 U.S. population >65, with a mean of approximately 1.3%.

Figure 78

The US 2018 Distribution of the Schizophrenia Prevalence Population Over 65

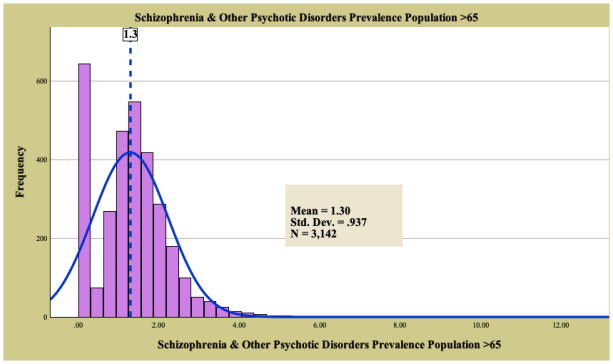
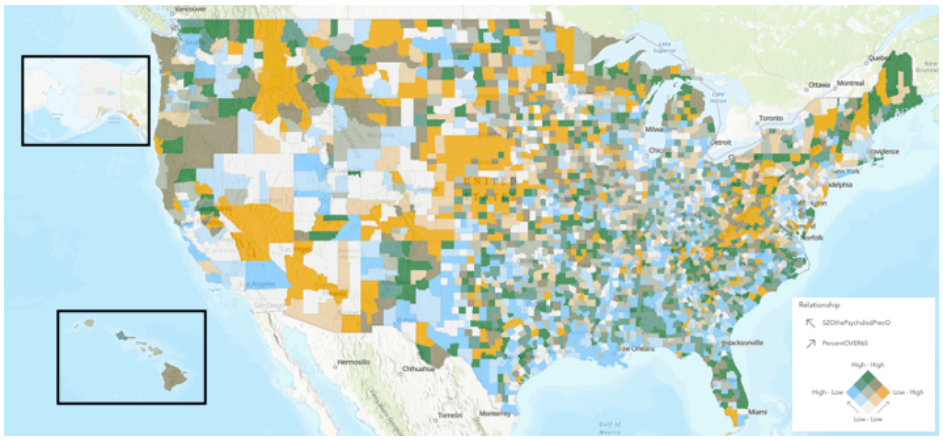


Figure 79 shows te geospatial distribution of SZ and other psychotic disorders prevalence for the 2018 U.S. general population above and below the mean (1.3%) converges with Table 14 and Figure 78. Orange shades point to areas with higher SZ

prevalence, as observed throughout the continental United States, including Hawaii and Alaska.

Figure 79

The US 2018 Geospatial Distribution of Schizophrenia and Other Psychotic Disorders Prevalence in the Population Over 65



Inferential Statistical and Geospatial Evaluation of the Relationships Between the Study Variables

As stated in Chapter 2, there is a large body of scientific literature that links T2DM, AH, SZ, and OP, all chronic diseases directly and indirectly related to ADRD development, onset, and prevalence. T2DM and related treatment promote bone mineral density loss (OP), which must be evaluated in relation to ADRD. (Ferrari et al., 2020; Jackulliak et al., 2019; Hagi et al., 2021; Holt, 2019; Moshin et al., 2019; Poiana & Capatina, 2017; Rehling et al.,2019; Sheu et al., 2022; Yuhao et al., 2019

In evaluating the association between the prevalence of ADRD, T2DM, AH, OP, and SZ, a correlation and related covariance analysis would inform this investigation of

the potential relationships among these diseases and whether their variation, from a linear model perspective, occurs in the same or opposite directions (covariance); and the strength of such association (correlation) via the Pearson's *R*. To these effects, R^2 renders a goodness of fit measure that points to the variation of the outcome justified by the variation in inputs.

Tables 15–20 show the mean and standard deviation for each disease prevalence (ADRD, T2DM, AH, OP, and SZ), and the confidence intervals of their Pearson's correlation for the U.S. population in 2018.

Table 15

Descriptive Statistics for the US 2018 Prevalence of ADRD, T2DM, AH, OP, and SZ

Descriptive Statistics

	Mean	Std. Deviation	N
ADRD Prevalence Total Population	9.965120	2.5948589	3142
T2DM Prevalence Total Population	26.359283	6.1495521	3142
Hypertension Prevalence Total Population	55.827127	11.4855967	3142
Osteoporosis Prevalence Total Population	5.371179	1.9271449	3142
Schizophrenia & Other Psychotic Disorders Prevalence Total Population	2.4210	1.29140	3142

Table 16

Confidence Intervals for Pearson's Correlation "R" Between the Prevalence of ADRD, T2DM, AH, OP, and SZ for the US 2018 General Population at 95%CI and p<.001

Confidence Intervals

	Pearson Correlation	Sig. (2-tailed)	95% Confidence Intervals (2-tailed)[a] Lower	Upper
ADRD Prevalence Total Population - T2DM Prevalence Total Population	.618	<.001	.596	.639
ADRD Prevalence Total Population - Hypertension Prevalence Total Population	.690	<.001	.672	.708
ADRD Prevalence Total Population - Osteoporosis Prevalence Total Population	.451	<.001	.422	.478
ADRD Prevalence Total Population - Schizophrenia & Other Psychotic Disorders Prevalence Total Population	.507	<.001	.480	.532
T2DM Prevalence Total Population - Hypertension Prevalence Total Population	.870	<.001	.862	.879
T2DM Prevalence Total Population - Osteoporosis Prevalence Total Population	.264	<.001	.231	.296
T2DM Prevalence Total Population - Schizophrenia & Other Psychotic Disorders Prevalence Total Population	.482	<.001	.455	.508
Hypertension Prevalence Total Population - Osteoporosis Prevalence Total Population	.392	<.001	.362	.421
Hypertension Prevalence Total Population - Schizophrenia & Other Psychotic Disorders Prevalence Total Population	.472	<.001	.445	.499
Osteoporosis Prevalence Total Population - Schizophrenia & Other Psychotic Disorders Prevalence Total Population	.234	<.001	.201	.267

a. Estimation is based on Fisher's r-to-z transformation with bias adjustment.

Table 17 shows the correlation and covariance, from a linear model perspective, between each disease prevalence (ADRD, T2DM, AH, OP, and SZ) in the United States for 2018.

The Pearson *R* values of correlation between each of these variables, and their respective R^2 values indicate that based only on the influence of T2DM could justify up to 38.2 % of ADRD prevalence. Hypertension (AH)prevalence alone could justify up to 48.86% of ADRD prevalence, OP could justify up to 20.34% of ADRD prevalence and

SZ and other psychotic disorders prevalence alone could justify up to 25.7 % of ADRD prevalence. These findings are significant, especially when observing the mean prevalence of these diseases at 95%CI, p< .05 (Table 15), where for the 2018 U.S. general population, the prevalence of ADRD was 9.965%, T2DM (26.36%), AH (55.83%), OP (5.37%), and SZ (2.42%).

Table 17

Correlation and Covariance Between the US 2018 Prevalence of ADRD, T2DM, AH, OP, and SZ

Correlations

		ADRD Prevalence Total Population	T2DM Prevalence Total Population	Hypertension Prevalence Total Population	Osteoporosis Prevalence Total Population	Schizophrenia & Other Psychotic Disorders Prevalence Total Population
ADRD Prevalence Total Population	Pearson Correlation	1	.618**	.690**	.451**	.507**
	Sig. (2-tailed)		<.001	<.001	<.001	<.001
	Sum of Squares and Cross-products	21149.273	30993.277	64630.698	7079.445	5333.500
	Covariance	6.733	9.867	20.576	2.254	1.698
	N	3142	3142	3142	3142	3142
T2DM Prevalence Total Population	Pearson Correlation	.618**	1	.870**	.264**	.482**
	Sig. (2-tailed)	<.001		<.001	<.001	<.001
	Sum of Squares and Cross-products	30993.277	118783.167	193100.912	9818.783	12024.685
	Covariance	9.867	37.817	61.478	3.126	3.828
	N	3142	3142	3142	3142	3142
Hypertension Prevalence Total Population	Pearson Correlation	.690**	.870**	1	.392**	.472**
	Sig. (2-tailed)	<.001	<.001		<.001	<.001
	Sum of Squares and Cross-products	64630.698	193100.912	414357.366	27276.457	22007.307
	Covariance	20.576	61.478	131.919	8.684	7.006
	N	3142	3142	3142	3142	3142
Osteoporosis Prevalence Total Population	Pearson Correlation	.451**	.264**	.392**	1	.234**
	Sig. (2-tailed)	<.001	<.001	<.001		<.001
	Sum of Squares and Cross-products	7079.445	9818.783	27276.457	11665.320	1828.401
	Covariance	2.254	3.126	8.684	3.714	.582
	N	3142	3142	3142	3142	3142
Schizophrenia & Other Psychotic Disorders Prevalence Total Population	Pearson Correlation	.507**	.482**	.472**	.234**	1
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	
	Sum of Squares and Cross-products	5333.500	12024.685	22007.307	1828.401	5238.323
	Covariance	1.698	3.828	7.006	.582	1.668
	N	3142	3142	3142	3142	3142

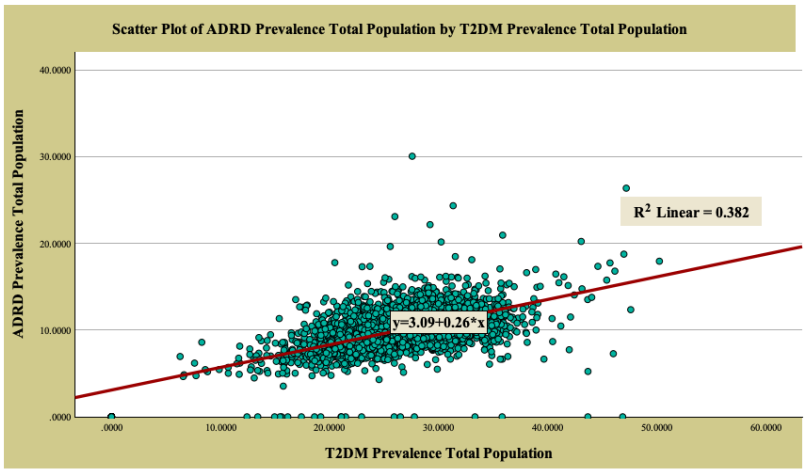
**. Correlation is significant at the 0.01 level (2-tailed).

The covariance between ADRD prevalence and T2DM, AH, OP, and SZ prevalence was positive in all cases. Thus, pointing to a positive relationship where the outcome ADRD prevalence grew in the same direction of growth of the prevalence of

those diseases. The scatter plots and geospatial distribution maps of Figures 80 - 87 show these relationships graphically.

Figure 80

Correlation Between US 2018 Prevalence of ADRD and T2DM (R^2 = 0.382)



T2DM prevalence alone, with R^2 = 0.382 could justify up to 38.2 % of ADRD prevalence. Both ADRD prevalence and T2DM prevalence increase in the same direction also observed in Figure 81 about the ADRD-T2DM prevalence relationship.

Figure 81 shows the US 2018 geospatial distribution of the relationship between the prevalence of ADRD and T2DM in the general population. Purple shade denotes the convergence of high ADRD and T2DM Prevalence.

Figure 81

The US 2018 Geospatial Distribution of the Relationship Between the Prevalence of ADRD and T2DM in the General Population

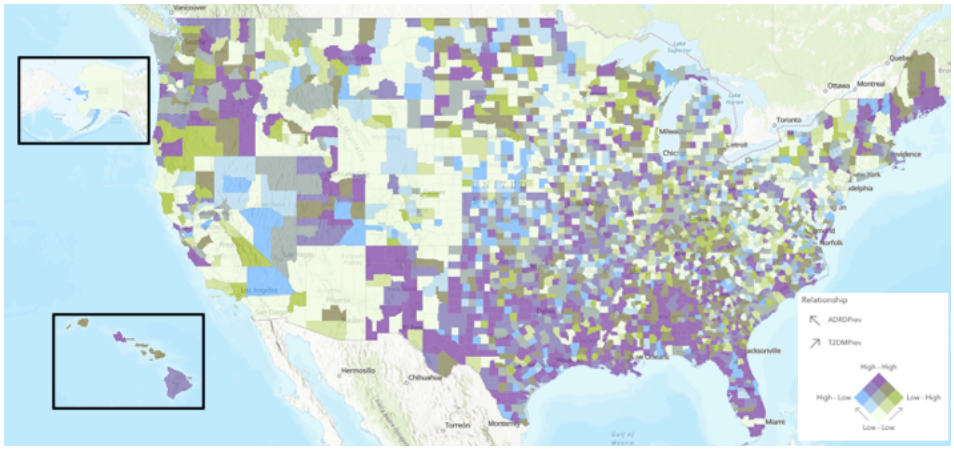


Figure 82 shows that hypertension prevalence alone, with $R^2 = 0.477$ could justify up to 47.7 % of ADRD prevalence. Both ADRD and hypertension prevalence increase in the same direction.

Figure 82

Correlation Between ADRD and Hypertension Prevalence ($R^2 = 0.477$).

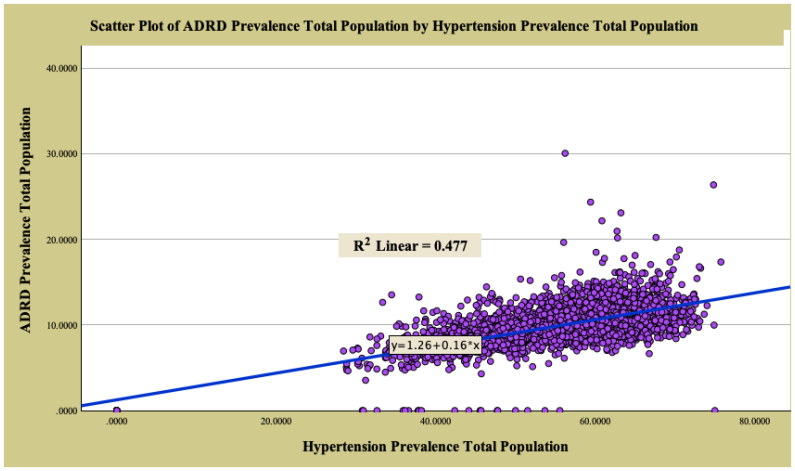


Figure 83 shows the geospatial distribution of the relationship between ADRD and Hypertension prevalence for the general US population in 2018.

Figure 83

The US 2018 Geospatial Distribution of the Relationship Between ADRD and Hypertension Prevalence in the Genera Population

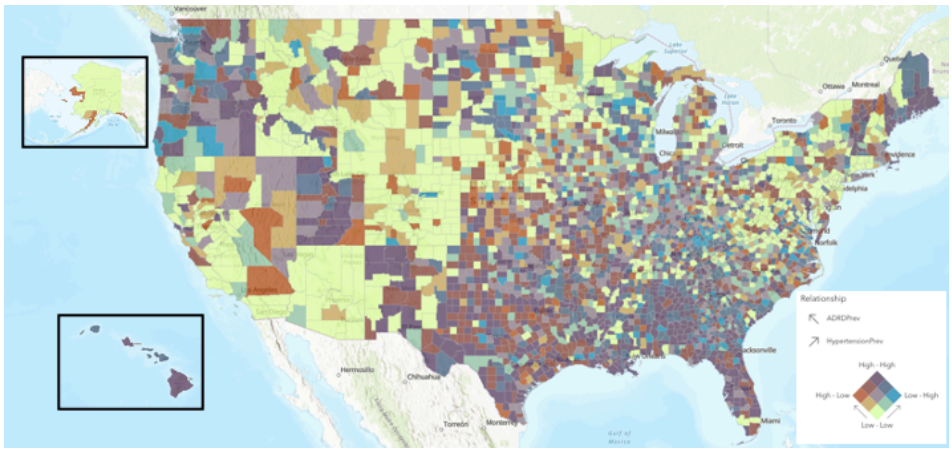


Figure 84 shows that osteoporosis prevalence alone, with $R^2 = 0.203$ could justify up to 20.3 % of ADRD prevalence. Both ADRD and Osteoporosis prevalence increase in the same direction.

Figure 84

Correlation between ADRD Prevalence and OP Prevalence (R^2 = 0.203).

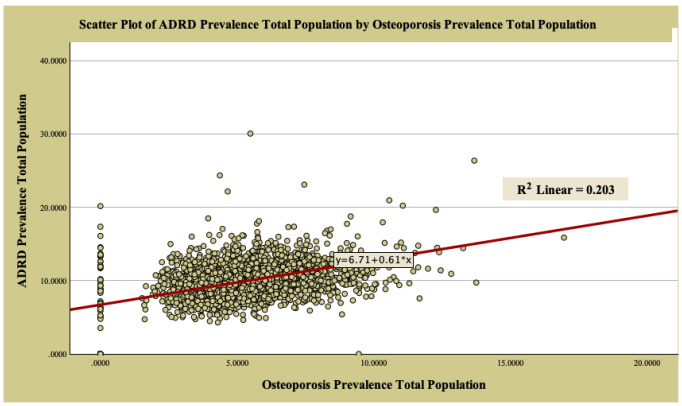


Figure 85 shows the US 2018 geospatial distribution of the relationship between ADRD and Osteoporosis prevalence for the general population.

Figure 85

The US 2018 Geospatial Distribution of the Relationship Between ADRD and Osteoporosis Prevalence in the General Population

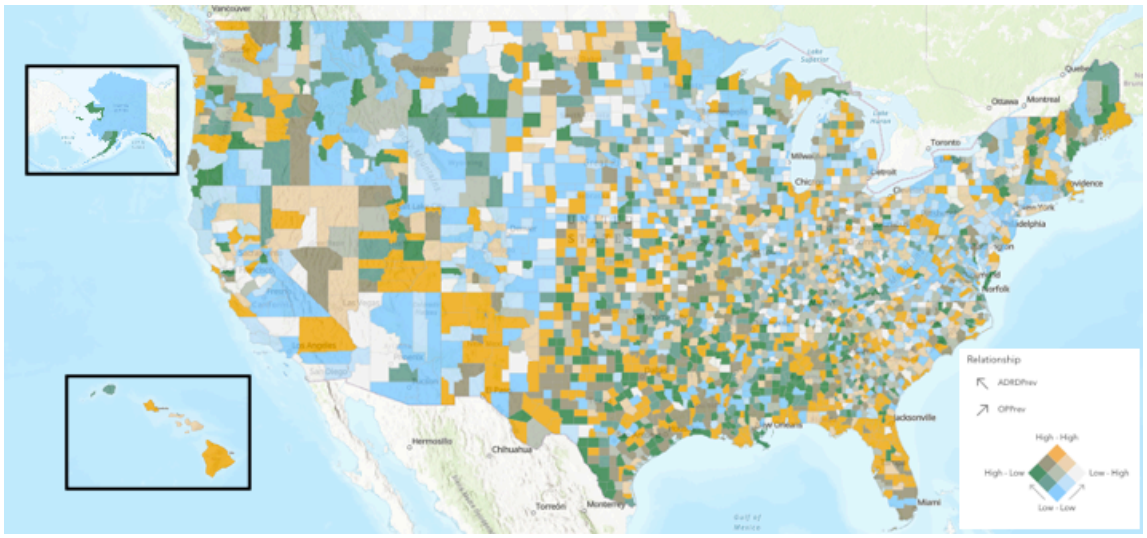
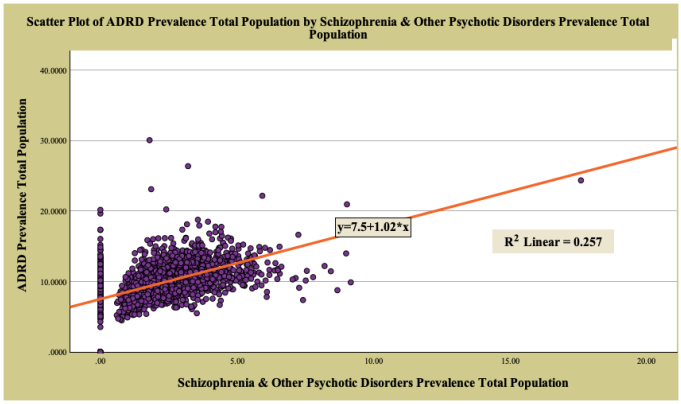


Figure 86

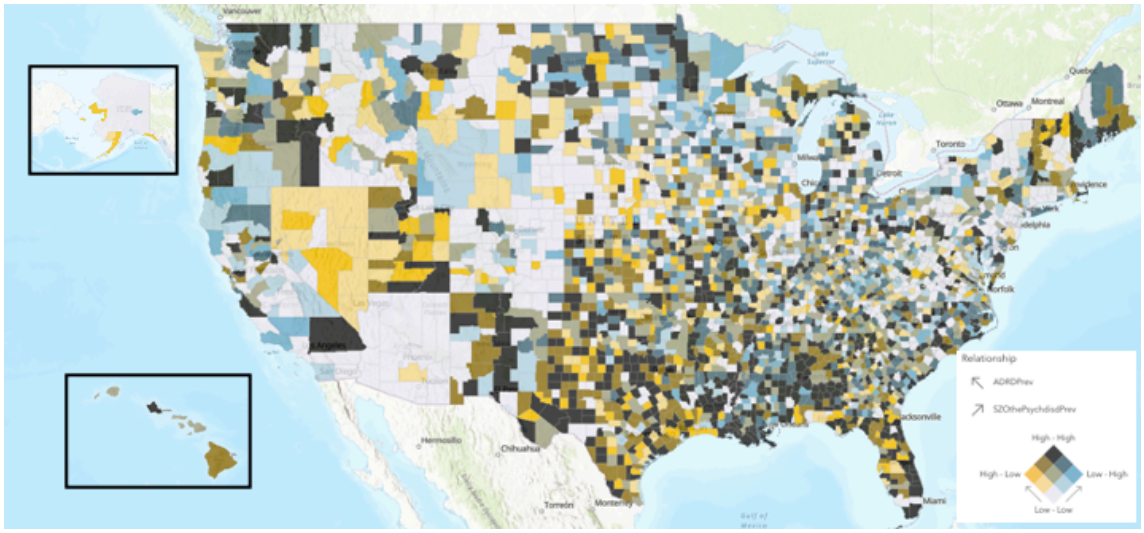
Correlation Between ADRD and Schizophrenia and Other Psychotic Disorders Prevalence (R^2 = 0.257)



SZ prevalence alone, with R^2 = 0.257 could justify up to 25.7 % of ADRD prevalence. Both ADRD prevalence and SZ prevalence increase in the same direction.

Figure 87

The US 2018 Geospatial Distribution of the Relationship Between ADRD and Schizophrenia and Other Psychotic Disorders Prevalence in the General Population



To these effects, and for the subsequent regression analyses of ADRD prevalence related to the influence of SDoH in the U.S. context of T2DM and AH, the above geospatial relationship analyses help elucidate the confluence of SDoH effects and ADRD prevalence.

Research Question 1

RQ1: Is there a statistically significant predictable relationship that exists between SdoH (education attainment, income, housing, and pollution) and the prevalence of ADRD in the United States?

$H_0$1: No, there is no statistically significant predictable relationship between SDoH (education attainment, income, housing, and pollution) and the prevalence of ADRD in the United States.

H_a1: Yes, there is a statistically significant predictable relationship between SDoH (education attainment, income, housing, and pollution) and the prevalence of ADRD in the United States.

Running an MLR analysis in SPSS v. 29, after controlling for age, gender, and ethnicity, revealed a statistically significant predictable relationship between ADRD prevalence in the general population where the influence of SDoH, behave in a linear model equivalent to Y= 9.97 + 0.77X, F(1,27) = 11.018, $p < .001$ with an $R^2 = 0.087$, and $adj\text{-}R^2 = 0.079$, could explain up to 8.7% of related ADRD prevalence (see Tables 19–21 and Figure 82). at a 95%CI and an effect size $f^2 = R^2/(1\text{-}R^2)$ =.096 ~0.1 which rendered a statistical power ($1\text{-}\beta$) ~99.99% calculated post-hoc. These results reject the null hypothesis in favor of the alternative.

Table 18

Descriptive Statistics of the Variables in the ADRD-SDoH MLR Model

Descriptive Statistics of ADRD-SDoH MLR Model

	Mean	Std. Deviation	N
ADRD Prevalence Total Population	9.965120	2.5948589	3142
Population Percent Smokers	17.8726	3.66004	3142
Population Percent Obese	31.474	4.5141	3142
Food Environment Index	7.364	1.3148	3142
Population Percent Food Insecure	14.139	4.2360	3142
Population Percent at 20th Percentile Income	20897.95	6230.447	3142
Income Ratio /Income Inequality	4.520	.7442	3142
Chlamydia Infection Rate	345.096	248.4230	3142
Percent of Cohort Graduating from High School	73.3014	31.66884	3142
Percen Population 25-44 with Some College	57.2305	11.55042	3142
Percent Population with Severe Housing Problems	14.4618	4.78948	3142
Age-Adjusted Mortality	393.015	122.6784	3142
Percent Adults Uninsured	14.2840	6.25362	3142
Health Care Costs	9608.72	1566.086	3142
Median Household Income	49506.35	12915.510	3142
Air_Pollution_PM25	8.855	1.8269	3142
Population Percent Rural	58.4515	31.56833	3142
County Health Behaviors Rank	46.76	41.715	3142
County Health Outcomes Rank	46.76	41.715	3142
Population Percent African-American (non-Hispanic Black)	8.9425	14.31113	3142
Population Percent American Indian / Alaskan Native (AIAN)	2.3094	7.72066	3142
Population Percent Asian	1.4856	2.85933	3142
Population Percent Native Hawaiian & Other Pacific Islander	.1349	.98500	3142
Population Percent Hispanic/Latino	9.2896	13.66175	3142
County Female Population Percentage 18-24	.0406	.01656	3142
County Female Population Percentage 25-44	.1135	.01606	3142
County Female Population Percentage 45-64	.1332	.01446	3142
County Female Population Percentage >65	.1038	.02393	3142

Table 19

MLR Model Summary for the ADRD-SDoH Relationship.

ADRD-SDoH MLR Model Summary[b]

					Change Statistics					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.295[a]	.087	.079	2.4898703	.087	11.018	27	3114	<.001	1.551

[a] Predictors: (Constant), County Female Population Percentage >65, Population Percent Food Insecure, Population Percent Native Hawaiian & Other Pacific Islander, Air_Pollution_PM25, County Health Outcomes Rank, Population Percent Asian , Percent of Cohort Graduating from High School, County Female Population Percentage 18-24, Population Percent American Indian / Alaskan Native (AIAN), Health Care Costs, Population Percent Hispanic/Latino, Population Percent Obese, Income Ratio /Income Inequality, Population Percent Rural, County Female Population Percentage 45-64, Percen Population 25-44 with Some College, Food Environment Index, Percent Population with Severe Housing Problems, Percent Adults Uninsured, Chlamydia Infection Rate, Age-Adjusted Mortality, Population Percent African-American

[b] Dependent Variable: ADRD Prevalence Total Population

Percent at 20th Percentile Income

Table 20

Table of β-Coefficients and Statistical Significance for the ADRD-SDoH MLR Model

Coefficients for the ADRD-SDoH MLR Model[a]

Model		Unstandardized Coefficients		Standardized Coefficients			Correlations			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	5.858	1.557		3.762	<.001					
	Population Percent Smokers	-.056	.024	-.079	-2.323	.020	.004	-.042	-.040	.256	3.913
	Population Percent Obese	.018	.015	.031	1.205	.228	.059	.022	.021	.433	2.307
	Food Environment Index	.033	.051	.017	.661	.509	-.056	.012	.011	.447	2.239
	Population Percent Food Insecure	.076	.025	.125	3.071	.002	.107	.055	.053	.178	5.632
	Population Percent at 20th Percentile Income	-3.698E-5	.000	-.089	-1.315	.189	-.088	-.024	-.023	.064	15.566
	Income Ratio /Income Inequality	-.021	.109	-.006	-.189	.850	.064	-.003	-.003	.298	3.359
	Chlamydia Infection Rate	.001	.000	.061	1.975	.048	.042	.035	.034	.308	3.246
	Percent of Cohort Graduating from High School	.002	.002	.020	.904	.366	.061	.016	.015	.604	1.655
	Percen Population 25-44 with Some College	.005	.007	.021	.668	.504	-.096	.012	.011	.296	3.381
	Percent Population with Severe Housing Problems	-.023	.014	-.043	-1.625	.104	-.031	-.029	-.028	.421	2.378
	Age-Adjusted Mortality	.000	.001	-.012	-.394	.694	.079	-.007	-.007	.310	3.221
	Percent Adults Uninsured	.086	.012	.207	7.430	<.001	.179	.132	.127	.378	2.646
	Health Care Costs	.000	.000	.106	4.872	<.001	.181	.087	.083	.616	1.624
	Median Household Income	3.172E-5	.000	.158	2.521	.012	-.081	.045	.043	.075	13.382
	Air_Pollution_PM25	.081	.035	.057	2.285	.022	.069	.041	.039	.476	2.102
	Population Percent Rural	.002	.002	.020	.713	.476	.002	.013	.012	.391	2.555
	County Health Behaviors Rank	-.002	.002	-.040	-1.174	.241	.120	-.021	-.020	.256	3.911
	County Health Outcomes Rank	.002	.002	.037	1.064	.287	.130	.019	.018	.243	4.110
	Population Percent African-American (non-Hispanic Black)	-.007	.006	-.040	-1.228	.220	.105	-.022	-.021	.281	3.560
	Population Percent American Indian / Alaskan Native (AIAN)	-.042	.010	-.124	-4.332	<.001	-.095	-.077	-.074	.359	2.787
	Population Percent Asian	-.051	.021	-.056	-2.456	.014	-.052	-.044	-.042	.559	1.790
	Population Percent Native Hawaiian & Other Pacific Islander	.141	.050	.053	2.811	.005	.010	.050	.048	.809	1.236
	Population Percent Hispanic/Latino	.004	.006	.019	.645	.519	.091	.012	.011	.338	2.958
	County Female Population Percentage 18-24	-2.674	3.982	-.017	-.672	.502	.003	-.012	-.011	.454	2.203
	County Female Population Percentage 25-44	-.735	5.048	-.005	-.146	.884	.025	-.003	-.002	.300	3.330
	County Female Population Percentage 45-64	-10.774	4.704	-.060	-2.290	.022	-.058	-.041	-.039	.427	2.344
	County Female Population Percentage >65	4.111	3.978	.038	1.034	.301	.002	.019	.018	.218	4.591

[a] Dependent Variable: ADRD Prevalence Total Population

It is worth mentioning here that while the statistical results reject the null hypothesis in favor of the alternative, some of the variables did not render a statistically significant contribution to the model's outcome ADRD prevalence (i.e., percentage of obese, FEI, 20th percentile income, income ratio, percentage of rural population, age-adjusted mortality, adults 25–44 with incomplete postsecondary education, HS graduation rate, percentage of severe housing problems, county's health behaviors and outcomes ranks). Population percentages by race/ethnicity showed that compared to non-Hispanic Whites, AIAN ($p < .001$) and Asians ($p < .014$) had an inverse, yet statistically significant, relationship to ADRD prevalence, except for the Hawaiian and other Pacific Islanders ($p < .005$) group, where the relationship correlated positively. Hispanic/Latinos and non-Hispanic Black population percentage were not statistically significant.

Regarding age and gender, only the percentage of the female population aged 45–64 showed a statistically significant ($p < .022$), yet inverse relationship to ADRD prevalence compared to females under 18.

Figure 88

MLR Model Plot for the ADRD Prevalence Associated With SDoH.

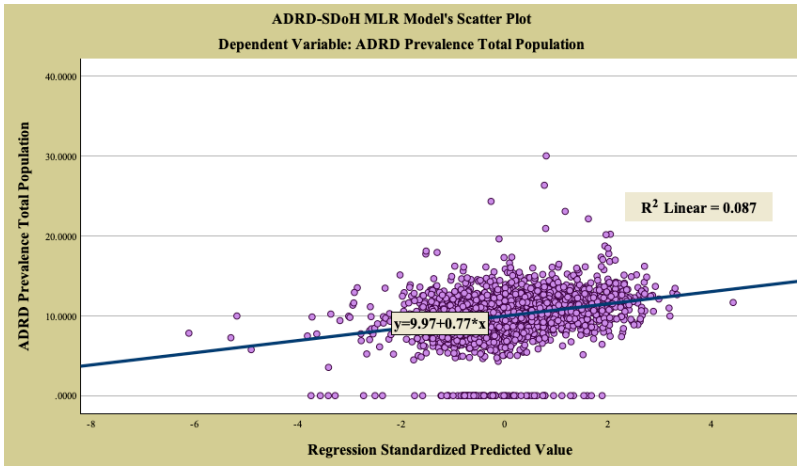


Table 21 shows the residual statistics for the ADRD-SDoH MLR Model converging with the scatter plot of Figure 88.

Table 21

The Residual Statistics for the ADRD-SDoH MLR Model.

Residuals Statistics for the ADRD-SDoH MLR Model[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	5.289432	13.354486	9.965120	.7662435	3142
Residual	-11.4133835	19.4485874	.0000000	2.4791458	3142
Std. Predicted Value	-6.102	4.423	.000	1.000	3142
Std. Residual	-4.584	7.811	.000	.996	3142

[a] Dependent Variable: ADRD Prevalence Total Population

GWR and MGWR statistical analysis, using ASU's MGWR 2.2.1, revealed a similar yet refined result to the previous MLR analysis. The MGWR analysis renders a more accurate model at the global and local scales with a AICc= 7441.890 and adj.R^2 =

0.138 where the influence of SDoH could explain up to 13.8% of related ADRD prevalence. These effects are better observed in Table 22 and Figures 89 – 91. Based on the autocorrelation normal distribution curve in Figure 89, the GWR and MGWR models are depicted in Figures 90 and 91, at the global (U.S.) and local (state/county) scales.

Table 22

Model Summary for the OLS, GWR, and MGWR Analysis of the ADRD-SDoH Relationships.

	GWR Model		MGWR Model	
ADRD Prevalence	**OLS**	**GWR**	**OLS**	**MGWR**
Adj. R^2	0.077	**0.154**	0.077	**0.138**
ACIc	7576.617	7483.904	7576.617	7441.890

Figure 89 shows the spatial auto correlation distribution curve with Moran's Index depicting critical z-cores, standard deviation, and p-values for CIs 90%-99%. Highlighted Cluster in Red denotes that given the z-score of 93.9832032098, there is a

less than 1% likelihood that this clustered pattern could be the result of random. Adapted from Bhunia & Shit, (2019).

Figure 89

Spatial Auto Correlation Curve With Moran's Index

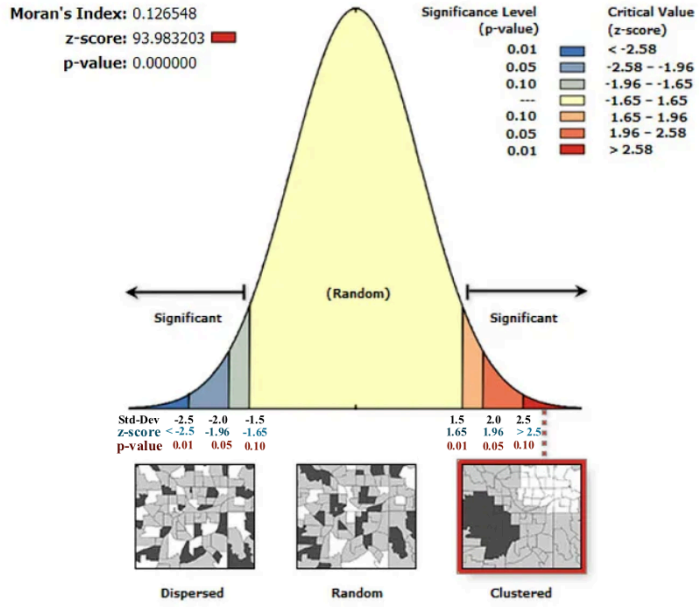


Figure 90 shows that at the local context level, the MGWR model (right) is more accurate than the GWR (left). The red circles show how areas of Texas, previously (GWR) assessed with lower ADRD prevalence, are brought to consideration via the MGWR model (right).

Figure 90

The Local Context of the MGWR Model Compared to the GWR (left).

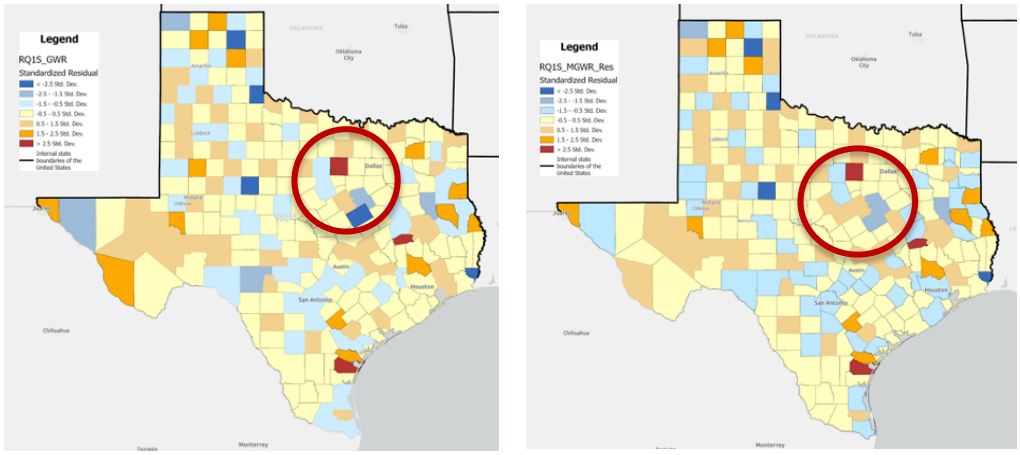
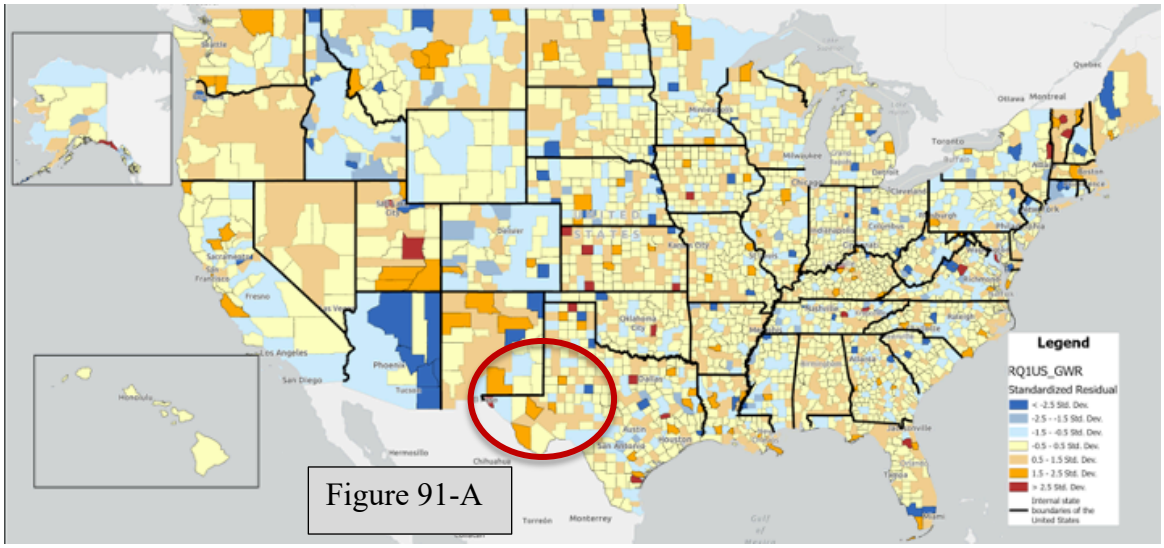


Figure 91 shows the *GWR model (A) compared to the MGWR (B) depicting subtle differences (i.e., Texas in red circle) due to the greater accuracy of the MGWR model.*

Figure 91

The GWR Model (A) Compared to the MGWR (B)



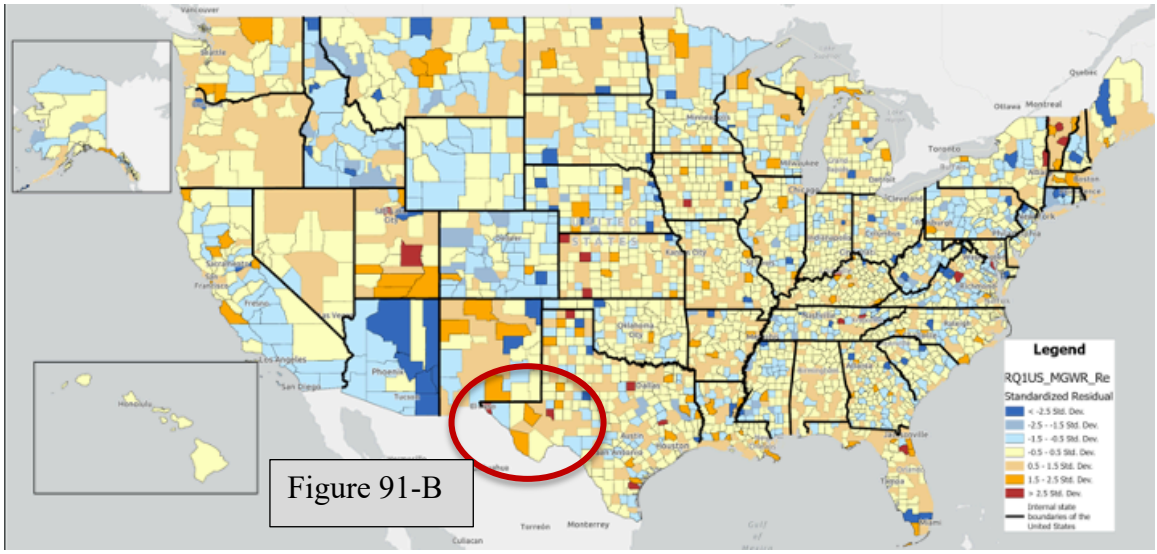


Figure 91-B

Hence, the above statistical and geospatial-statistical analyses, Table 20 and Appendix D, point to an MRL model as follows:

$$Y_{ADRD\_Prev} = \beta_o + \beta_{smokers}\,(Smokers_{\%}) + \beta_{FI}(FI_{\%}) + \beta_{Chlamydia}(Chlamydia_{RATE}) + \beta_{Uninsured\_Adults}\,(Uninsured\ Adults_{\%}) + \beta_{HCCosts}\,(HC_{Costs}) + \beta_{MHIncome}(MHIncome) + \beta_{PM2.5}\,(PM_{2.5}) + \beta_{AIAN}\,(AIAN_{\%}) + \beta_{Asians}\,(Asians_{\%}) + \beta_{HoPIs}(HawaiiansPIs_{\%}) + \beta_{FEM45\text{-}64}\,(FEM_{45\text{-}64\,\%})$$

$$Y_{ADRD\_Prev} = 5.858 - 0.56(Smokers_{\%}) + 0.76(FI_{\%}) + 0.001(Chlamydia_{RATE}) + 0.086(Uninsured\ Adults_{\%}) + 0.0001(HC_{Costs}) + 3.17\mathbf{E\text{-}5}(MHIncome) + 0.081(PM_{2.5}) + 0.042(AIAN_{\%}) + 0.086\,(Asians_{\%}) + 0.141 HawaiiansPIs_{\%}) - 10.774\,(FEM_{45\text{-}64\,\%})$$

Research Question 2

RQ2**:** Is there a statistically significant predictable statistical relationship that exists between T2DM and the prevalence of ADRD in the United States?

$H_0$2: No, there is no statistically significant predictable relationship between T2DM and the prevalence of ADRD in the United States.

H_a2: Yes, there is a statistically significant predictable relationship between T2DM and the prevalence of ADRD in the United States.

The required MLR analysis in SPSS v. 29, after controlling for age, gender, and ethnicity, to answer this question, revealed a statistically significant predictable relationship between ADRD prevalence in the general population where the influence of SDoH, behave in linear model equivalent to Y= 9.97 + 0.147X, F(1, 29) = 51.212, $p < .001$ with an $R^2 = 0.323$, and adj-$R^2 = 0.317$, could explain up to 32.3% of related ADRD prevalence (see Tables 24–26 and Figure 83). at a 95%CI and an effect size $f^2 = R^2/(1-R^2) = 0.477$ which rendered a statistical power ($1-\beta$) ~99.99% calculated post-hoc. These results reject the null hypothesis in favor of the alternative.

Table 23 shows the Descriptive statistics of the variables evaluated in the ADRD-SDoH and T2DM prevalence model via MLR analysis in SPSS v.29 at 95%CI.

Table 23

Descriptive Statistics of the Variables in the ADRD-SDoH and T2DM Prevalence MLR Model

Descriptive Statistics

	Mean	Std. Deviation	N
ADRD Prevalence Total Population	9.965120	2.5948589	3142
Population Percent Smokers	17.8726	3.66004	3142
Population Percent Obese	31.474	4.5141	3142
Food Environment Index	7.364	1.3148	3142
Population Percent Food Insecure	14.139	4.2360	3142
Population Percent at 20th Percentile Income	20897.95	6230.447	3142
Income Ratio /Income Inequality	4.520	.7442	3142
Chlamydia Infection Rate	345.096	248.4230	3142
Percent of Cohort Graduating from High School	73.3014	31.66884	3142
Percen Population 25-44 with Some College	57.2305	11.55042	3142
Percent Population with Severe Housing Problems	14.4618	4.78948	3142
Age-Adjusted Mortality	393.015	122.6784	3142
Percent Adults Uninsured	14.2840	6.25362	3142
Health Care Costs	9608.72	1566.086	3142
Median Household Income	49506.35	12915.510	3142
Air_Pollution_PM25	8.855	1.8269	3142
Population Percent Rural	58.4515	31.56833	3142
County Health Behaviors Rank	46.76	41.715	3142
County Health Outcomes Rank	46.76	41.715	3142
Population Percent African-American (non-Hispanic Black)	8.9425	14.31113	3142
Population Percent American Indian / Alaskan Native (AIAN)	2.3094	7.72066	3142
Population Percent Asian	1.4856	2.85933	3142
Population Percent Native Hawaiian & Other Pacific Islander	.1349	.98500	3142
Population Percent Hispanic/Latino	9.2896	13.66175	3142
County Female Population Percentage 18-24	.0406	.01656	3142
County Female Population Percentage 25-44	.1135	.01606	3142
County Female Population Percentage 45-64	.1332	.01446	3142
County Female Population Percentage >65	.1038	.02393	3142
T2DM Prevalence Population <65	24.8078	8.24493	3142
T2DM Prevalence Population >65	25.5013	8.38433	3142

Table 24

MLR Model Summary of the ADRD-SDoH & T2DM Prevalence Relationships.

Model Summary[b]

					Change Statistics					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.568[a]	.323	.317	2.1448839	.323	51.212	29	3112	<.001	1.659

a. Predictors: (Constant), T2DM Prevalence Population >65, Population Percent Rural, Population Percent Native Hawaiian & Other Pacific Islander, County Health Behaviors Rank, Population Percent American Indian / Alaskan Native (AIAN), Population Percent African-American (non-Hispanic Black), County Female Population Percentage 18-24, Health Care Costs, Population Percent Hispanic/Latino, Percent of Cohort Graduating from High School, Population Percent Asian , Income Ratio /Income Inequality, Food Environment Index, Population Percent Obese, County Female Population Percentage 25-44, County Female Population Percentage 45-64, Air_Pollution_PM25, Percent Population with Severe Housing Problems, Age-Adjusted Mortality, Percent Adults Uninsured, Percen Population 25-44 with Some College, Chlamydia Infection Rate, Population Percent Smokers, County Female Population Percentage >65, County Health Outcomes Rank, Median Household Income, T2DM Prevalence Population <65, Population Percent Food Insecure, Population Percent at 20th Percentile Income

b. Dependent Variable: ADRD Prevalence Total Population

Table 25

Table of β-Coefficients and Statistical Significance for the ADRD-SDoH and T2DM MLR Model.

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			Correlations			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	4.125	1.343		3.072	.002					
	Population Percent Smokers	-.042	.021	-.059	-2.004	.045	.004	-.036	-.030	.255	3.925
	Population Percent Obese	.009	.013	.016	.715	.475	.059	.013	.011	.433	2.308
	Food Environment Index	.050	.044	.025	1.149	.251	-.056	.021	.017	.446	2.240
	Population Percent Food Insecure	.078	.021	.127	3.619	<.001	.107	.065	.053	.177	5.650
	Population Percent at 20th Percentile Income	-1.382E-5	.000	-.033	-.570	.569	-.088	-.010	-.008	.064	15.587
	Income Ratio /Income Inequality	-.089	.094	-.026	-.949	.343	.064	-.017	-.014	.297	3.363
	Chlamydia Infection Rate	.001	.000	.049	1.836	.066	.042	.033	.027	.308	3.247
	Percent of Cohort Graduating from High School	-.002	.002	-.019	-.986	.324	.061	-.018	-.015	.601	1.664
	Percen Population 25-44 with Some College	.007	.006	.031	1.136	.256	-.096	.020	.017	.296	3.381
	Percent Population with Severe Housing Problems	-.022	.012	-.041	-1.812	.070	-.031	-.032	-.027	.419	2.386
	Age-Adjusted Mortality	.000	.001	-.021	-.803	.422	.079	-.014	-.012	.310	3.231
	Percent Adults Uninsured	.070	.010	.169	7.015	<.001	.179	.125	.103	.377	2.653
	Health Care Costs	.000	.000	.093	4.949	<.001	.181	.088	.073	.616	1.625
	Median Household Income	2.109E-5	.000	.105	1.942	.052	-.081	.035	.029	.075	13.422
	Air_Pollution_PM25	-.003	.030	-.002	-.109	.913	.069	-.002	-.002	.472	2.117
	Population Percent Rural	-.001	.002	-.011	-.472	.637	.002	-.008	-.007	.390	2.562
	County Health Behaviors Rank	-.002	.002	-.032	-1.089	.276	.120	-.020	-.016	.256	3.914
	County Health Outcomes Rank	.003	.002	.048	1.611	.107	.130	.029	.024	.243	4.124
	Population Percent African-American (non-Hispanic Black)	-.012	.005	-.067	-2.417	.016	.105	-.043	-.036	.279	3.582
	Population Percent American Indian / Alaskan Native (AIAN)	-.027	.008	-.080	-3.224	.001	-.095	-.058	-.048	.357	2.800
	Population Percent Asian	-.027	.018	-.030	-1.505	.132	-.052	-.027	-.022	.557	1.794
	Population Percent Native Hawaiian & Other Pacific Islander	.044	.043	.017	1.014	.311	.010	.018	.015	.805	1.242
	Population Percent Hispanic/Latino	.003	.005	.014	.536	.592	.091	.010	.008	.338	2.959
	County Female Population Percentage 18-24	-3.009	3.431	-.019	-.877	.381	.003	-.016	-.013	.454	2.203
	County Female Population Percentage 25-44	-4.729	4.350	-.029	-1.087	.277	.025	-.019	-.016	.300	3.332
	County Female Population Percentage 45-64	-10.928	4.054	-.061	-2.696	.007	-.058	-.048	-.040	.426	2.345
	County Female Population Percentage >65	2.962	3.427	.027	.864	.388	.002	.015	.013	.218	4.592
	T2DM Prevalence Population <65	.043	.011	.138	3.995	<.001	.503	.071	.059	.182	5.486
	T2DM Prevalence Population >65	.117	.011	.378	10.791	<.001	.516	.190	.159	.178	5.632

[a] Dependent Variable: ADRD Prevalence Total Population

As the null hypothesis is rejected in favor of the alternative, it is worth mentioning that some of the variables did not render a statistically significant contribution to the model's outcome ADRD prevalence (i.e., percentage of obese, FEI, 20th percentile income, income ratio, chlamydia rate, percentage of rural population, age-adjusted mortality, adults 25–44 with incomplete postsecondary education, HS graduation rate, percentage of severe housing problems, air pollution, county's health behaviors and outcomes ranks). Population percentages by race/ethnicity showed that, compared to non-Hispanic Whites, only non-Hispanic Blacks and AIAN showed a

statistically significant and inverse relationship to the outcome (ADRD prevalence). Regarding age and gender, only the percentage of the female population aged 45–64 showed a statistically significant ($p < .007$), yet inverse, relationship to ADRD prevalence compared to females under 18.

Table 26 shows the *The Residual Statistics of the MLR Model for the ADRD-SDoH and T2DM relationships converging with the statistics as used in the scatter plot of Figure 92.*

Table 26

The Residual Statistics of the MLR Model for the ADRD-SDoH and T2DM Relationships

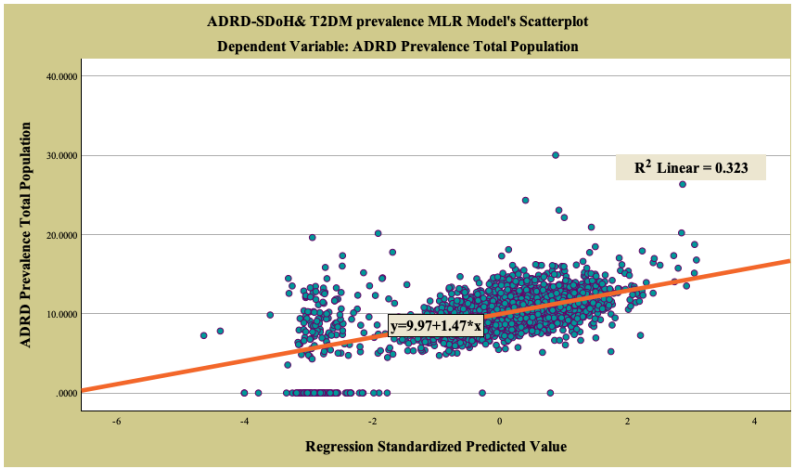
Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	3.125835	14.515599	9.965120	1.4748700	3142
Residual	-11.1386442	18.7720776	.0000000	2.1349593	3142
Std. Predicted Value	-4.637	3.085	.000	1.000	3142
Std. Residual	-5.193	8.752	.000	.995	3142

a. Dependent Variable: ADRD Prevalence Total Population

Figure 92

MLR Model Plot for the SDoH, ADRD, and T2DM Prevalence.



The GWR and MGWR statistical analysis, using ASU's MGWR 2.2.1, revealed the following refined result to the above MLR analysis:

Table 27

Model Summary for the OLS, GWR, and MGWR Analysis of the ADRD-SDoH and T2DM Relationships.

	GWR Model		MGWR Model	
ADRD Prevalence	**OLS**	**GWR**	**OLS**	**MGWR**
Adj. R^2	0.294	**0.360**	0.294	**0.482**
ACIc	6843.507	6743.084	6843.507	6290.112

The MGWR analysis renders a more accurate model at the global and local scales with a *AICc= 6290.112 and adj. R^2 = 0.482* where the influence of SDoH and T2DM prevalence could explained up to 48.2% of related ADRD prevalence. These effects are better observed in Figures 93 and 94.

Figure 93 shows that at the local context level, the MGWR model (right) is more accurate than the GWR (left). The red circles show how areas of Texas, previously (GWR) assessed with lower ADRD prevalence, are brought to consideration via the MGWR model (right).

Figure 93

The Local Context of the MGWR Model Compared to the GWR (left).

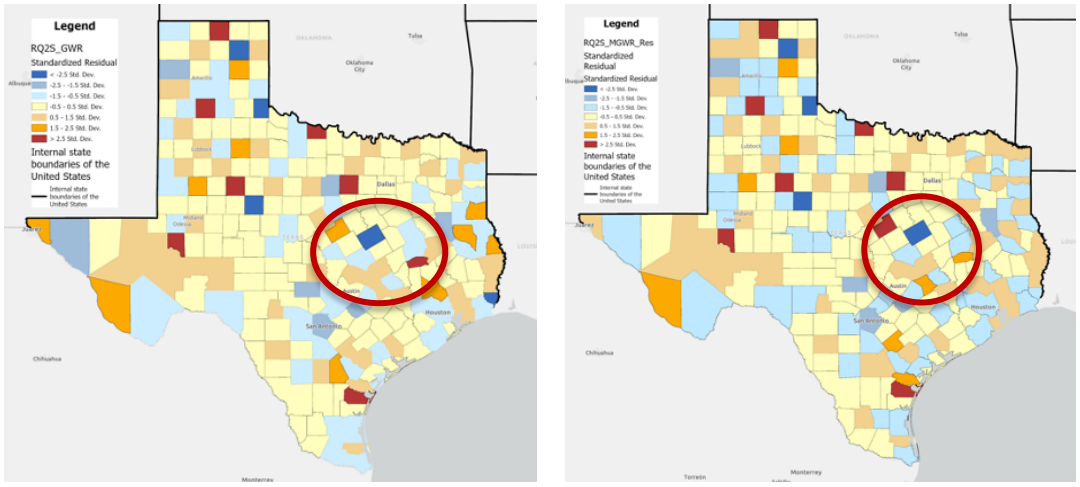
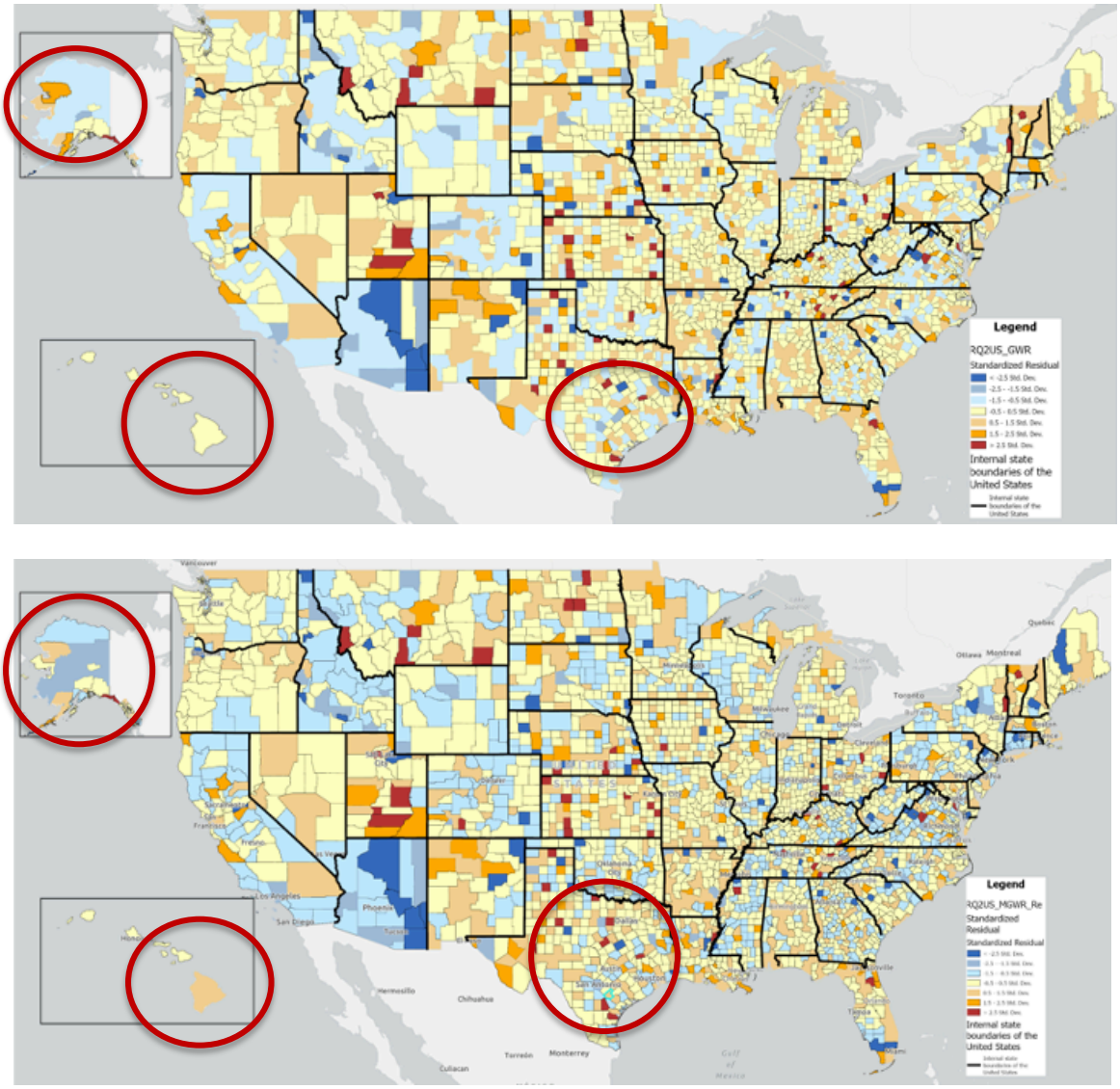


Figure 94 shows the GWR model (A) compared to MGWR (B) depicting subtle differences (i.e., Alaska, Hawaii, and Texas in red circles) due to the greater accuracy of the MGWR model.

Figure 94

The GWR Model (A) Compared to the MGWR (B)



Hence, the above statistical and geospatial-statistical analyses, Table 25, and Appendix E, point to an MLR model as follows:

$$Y_{ADRD\_Prev} = \beta_o + \beta_{smokers}\,(Smokers_{\%}) + \beta_{FI}(FI_{\%}) + \beta_{Uninsured\_Adults}\,(Uninsured\ Adults_{\%}) + \beta_{HCCosts}\,(HC_{Costs}) + \beta_{Blacks}\,(Blacks_{\%}) + \beta_{AIAN}\,(AIAN_{\%}) + \beta_{FEM4564}(FEM_{45064\%}) + \beta_{<65T2DM\%}(T2DM_{<65\%}) + \beta_{>65T2DM\%}(T2DM_{>65\%})$$

$$Y_{ADRD\_Prev} = 4.125 - 0.42\,(Smokers_{\%}) + 0.78(FI_{\%}) + 0.070(Uninsured\ Adults_{\%}) + 0.0001(HC_{Costs}) - 0.012(Blacks_{\%}) - 0.027(AIAN_{\%}) - 10.928(FEM_{45064\%}) + 0.043(T2DM_{<65\%}) + 0.117(T2DM_{>65\%})$$

Research Question 3

RQ3: Is there a statistically significant predictable relationship that exists between AH and the prevalence of ADRD in the United States?

$H_0$3: No, there is no statistically significant predictable relationship between AH and the prevalence of ADRD in the United States.

H_a3: Yes, there is a statistically significant statistically predictable relationship between AH and the prevalence of ADRD in the United States.

The required MLR analysis in SPSS v. 29, after controlling for age, gender, and ethnicity, to answer this question, revealed a statistically significant predictable relationship between ADRD prevalence in the general population where the influence of SDoH, behaves in linear model equivalent to Y= 9.97 + 0.164X, F(1, 29) = 71.972, $p < .001$ with an $R^2 = 0.401$, and $adj\text{-}R^2 = 0.396$, could explain up to 40.1% of ADRD prevalence (see Table 28–31 and Figure 95). at a 95%CI and an effect size $f^2 = R^2/(1\text{-}R^2) = 0.669$ which rendered a statistical power ($1\text{-}\beta$) ~99.99% calculated post-hoc. These results reject the null hypothesis in favor of the alternative.

Table 28

Descriptive Statistics of the Variables in the MLR Model of SDoH-ADRD and Hypertension Prevalence

Descriptive Statistics

	Mean	Std. Deviation	N
ADRD Prevalence Total Population	9.965120	2.5948589	3142
Population Percent Smokers	17.8726	3.66004	3142
Population Percent Obese	31.474	4.5141	3142
Food Environment Index	7.364	1.3148	3142
Population Percent Food Insecure	14.139	4.2360	3142
Population Percent at 20th Percentile Income	20897.95	6230.447	3142
Income Ratio /Income Inequality	4.520	.7442	3142
Chlamydia Infection Rate	345.096	248.4230	3142
Percent of Cohort Graduating from High School	73.3014	31.66884	3142
Percen Population 25-44 with Some College	57.2305	11.55042	3142
Percent Population with Severe Housing Problems	14.4618	4.78948	3142
Age-Adjusted Mortality	393.015	122.6784	3142
Percent Adults Uninsured	14.2840	6.25362	3142
Health Care Costs	9608.72	1566.086	3142
Median Household Income	49506.35	12915.510	3142
Air_Pollution_PM25	8.855	1.8269	3142
Population Percent Rural	58.4515	31.56833	3142
County Health Behaviors Rank	46.76	41.715	3142
County Health Outcomes Rank	46.76	41.715	3142
Population Percent African-American (non-Hispanic Black)	8.9425	14.31113	3142
Population Percent American Indian / Alaskan Native (AIAN)	2.3094	7.72066	3142
Population Percent Asian	1.4856	2.85933	3142
Population Percent Native Hawaiian & Other Pacific Islander	.1349	.98500	3142
Population Percent Hispanic/Latino	9.2896	13.66175	3142
County Female Population Percentage 18-24	.0406	.01656	3142
County Female Population Percentage 25-44	.1135	.01606	3142
County Female Population Percentage 45-64	.1332	.01446	3142
County Female Population Percentage >65	.1038	.02393	3142
Hypertension Prevalence Population <65	40.863915	12.8963573	3142
Hypertension Prevalence Population >65	57.057662	15.6214096	3142

Table 29

MLR Model Summary of the SDoH -ADRD and Hypertension Prevalence Relationships.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.634[a]	.401	.396	2.0168793	.401	71.972	29	3112	<.001	1.709

a. Predictors: (Constant), Hypertension Prevalence Population >65, Population Percent Rural, Population Percent Native Hawaiian & Other Pacific Islander, County Health Behaviors Rank, Population Percent American Indian / Alaskan Native (AIAN), Population Percent African-American (non-Hispanic Black), County Female Population Percentage 18-24, Health Care Costs, Population Percent Hispanic/Latino, Percent of Cohort Graduating from High School, Population Percent Asian , Income Ratio /Income Inequality, Food Environment Index, Population Percent Obese, County Female Population Percentage 25-44, County Female Population Percentage 45-64, Air_Pollution_PM25, Percent Population with Severe Housing Problems, Age-Adjusted Mortality, Percent Adults Uninsured, Percen Population 25-44 with Some College, Chlamydia Infection Rate, Population Percent Smokers, County Female Population Percentage >65, County Health Outcomes Rank, Median Household Income, Population Percent Food Insecure, Hypertension Prevalence Population <65, Population Percent at 20th Percentile Income

b. Dependent Variable: ADRD Prevalence Total Population

Table 30

Table of β-Coefficients and Statistical Significance for theMLR Mode of the SDoH - ADRD and Hypertension Prevalence

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	3.700	1.263		2.930	.003					
	Population Percent Smokers	-.048	.019	-.068	-2.479	.013	.004	-.044	-.034	.255	3.914
	Population Percent Obese	.004	.012	.007	.327	.744	.059	.006	.005	.433	2.309
	Food Environment Index	.047	.041	.024	1.147	.252	-.056	.021	.016	.447	2.240
	Population Percent Food Insecure	.077	.020	.126	3.837	<.001	.107	.069	.053	.177	5.638
	Population Percent at 20th Percentile Income	-4.857E-6	.000	-.012	-.213	.831	-.088	-.004	-.003	.064	15.588
	Income Ratio /Income Inequality	-.068	.089	-.019	-.765	.444	.064	-.014	-.011	.297	3.364
	Chlamydia Infection Rate	.000	.000	.022	.868	.386	.042	.016	.012	.307	3.256
	Percent of Cohort Graduating from High School	-.001	.001	-.011	-.626	.532	.061	-.011	-.009	.603	1.659
	Percen Population 25-44 with Some College	.005	.006	.024	.929	.353	-.096	.017	.013	.296	3.381
	Percent Population with Severe Housing Problems	-.028	.012	-.051	-2.376	.018	-.031	-.043	-.033	.420	2.379
	Age-Adjusted Mortality	-.001	.001	-.033	-1.331	.183	.079	-.024	-.018	.310	3.223
	Percent Adults Uninsured	.057	.009	.138	6.040	<.001	.179	.108	.084	.370	2.704
	Health Care Costs	.000	.000	.085	4.797	<.001	.181	.086	.067	.615	1.626
	Median Household Income	1.420E-5	.000	.071	1.392	.164	-.081	.025	.019	.075	13.407
	Air_Pollution_PM25	-.055	.029	-.039	-1.918	.055	.069	-.034	-.027	.469	2.132
	Population Percent Rural	-.002	.002	-.024	-1.066	.287	.002	-.019	-.015	.390	2.561
	County Health Behaviors Rank	-.001	.002	-.018	-.647	.518	.120	-.012	-.009	.256	3.914
	County Health Outcomes Rank	.003	.002	.048	1.714	.087	.130	.031	.024	.243	4.115
	Population Percent African-American (non-Hispanic Black)	-.011	.005	-.061	-2.312	.021	.105	-.041	-.032	.281	3.562
	Population Percent American Indian / Alaskan Native (AIAN)	-.021	.008	-.064	-2.739	.006	-.095	-.049	-.038	.357	2.799
	Population Percent Asian	-.025	.017	-.028	-1.489	.137	-.052	-.027	-.021	.558	1.793
	Population Percent Native Hawaiian & Other Pacific Islander	.018	.041	.007	.439	.661	.010	.008	.006	.803	1.246
	Population Percent Hispanic/Latino	.007	.005	.037	1.559	.119	.091	.028	.022	.337	2.965
	County Female Population Percentage 18-24	-2.617	3.226	-.017	-.811	.417	.003	-.015	-.011	.454	2.203
	County Female Population Percentage 25-44	-3.317	4.090	-.021	-.811	.417	.025	-.015	-.011	.300	3.331
	County Female Population Percentage 45-64	-9.300	3.811	-.052	-2.440	.015	-.058	-.044	-.034	.427	2.344
	County Female Population Percentage >65	2.602	3.226	.024	.807	.420	.002	.014	.011	.217	4.602
	Hypertension Prevalence Population <65	.015	.008	.075	1.964	.050	.569	.035	.027	.132	7.555
	Hypertension Prevalence Population >65	.086	.006	.520	13.725	<.001	.591	.239	.190	.134	7.451

a. Dependent Variable: ADRD Prevalence Total Population

As the null hypothesis is rejected in favor of the alternative, it is worth mentioning that some of the variables did not render a statistically significant contribution to the model's outcome ADRD prevalence (i.e., percentage of obese, FEI, 20th percentile income, income ratio, chlamydia rate, percentage of rural population, age-adjusted mortality, adults 25–44 with incomplete postsecondary education, HS graduation rate, percentage of severe housing problems, air pollution, county's health behaviors and outcomes ranks). Population percentages by race/ethnicity showed that, compared to non-Hispanic Whites, only non-Hispanic Blacks and AIAN showed a statistically significant and inverse relationship to the outcome (ADRD prevalence). Regarding age and gender, only women aged 45–64 showed a statistically significant ($p <$ .007), yet inverse, relationship to ADRD prevalence compared to females under 18.

Table 31 shows the residual statistics of the MLR model of the SDoH-ADRD and Hypertension Prevalence relationships depicting the statistics as used in the scatter plot of Figure 95.

Table 31

The Residual Statistics of the MLR Model for the SDoH-ADRD and Hypertension Prevalence

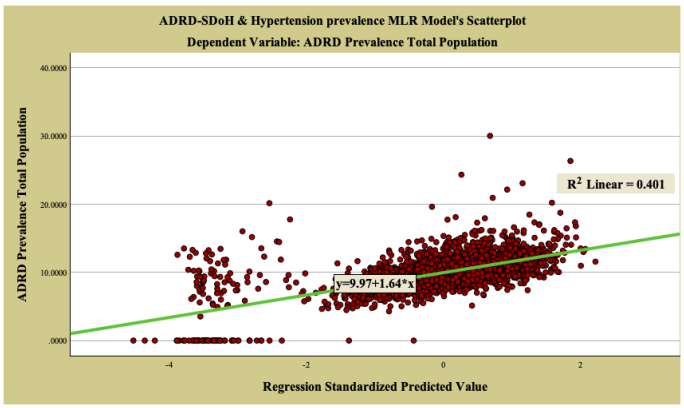
Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	2.527805	13.609488	9.965120	1.6440947	3142
Residual	-9.2508459	18.9516010	.0000000	2.0075471	3142
Std. Predicted Value	-4.524	2.217	.000	1.000	3142
Std. Residual	-4.587	9.396	.000	.995	3142

a. Dependent Variable: ADRD Prevalence Total Population

Figure 95

MLR Model Plot for the SDoH-ADRD and. Hypertension Prevalence



The GWR and MGWR statistical analysis, using ASU's MGWR 2.2.1, revealed the following refined result to the above MLR analysis:

Table 32

Model Summary for the OLS, GWR, and MGWR Analysis of the SDoH-ADRD and Hypertension Prevalence Relationships

	GWR Model		MGWR Model	
ADRD Prevalence	**OLS**	**GWR**	**OLS**	**MGWR**
Adj. R^2	0.396	**0.449**	0.372	**0.518**
ACIc	7366.691	7270.241	6526.092	6068.926

The MGWR analysis renders a more accurate local model with an AICc = 6068.926 and *adj.* R^2 = 0.518 where the influence of SDoH and T2DM prevalence could explain up to 51.8% of related ADRD prevalence at a 95%CI and an effect size $f^2 = R^2/(1-R^2)$ = 1.075 which rendered a statistical power ($1-\beta$) ~99.99% calculated post-hoc. These results further confirm the rejection of the null hypothesis for RQ3 in favor of the

alternative. These effects are better observed in 96 and 97.

Figure 96 shows that at the local context level, the MGWR model (right) is more accurate than the GWR (left). The red circles show how areas of Texas, previously (GWR) assessed with lower ADRD prevalence, are brought to consideration via the MGWR model (right).

Figure 96

The MGWR Model Compared to the GWR

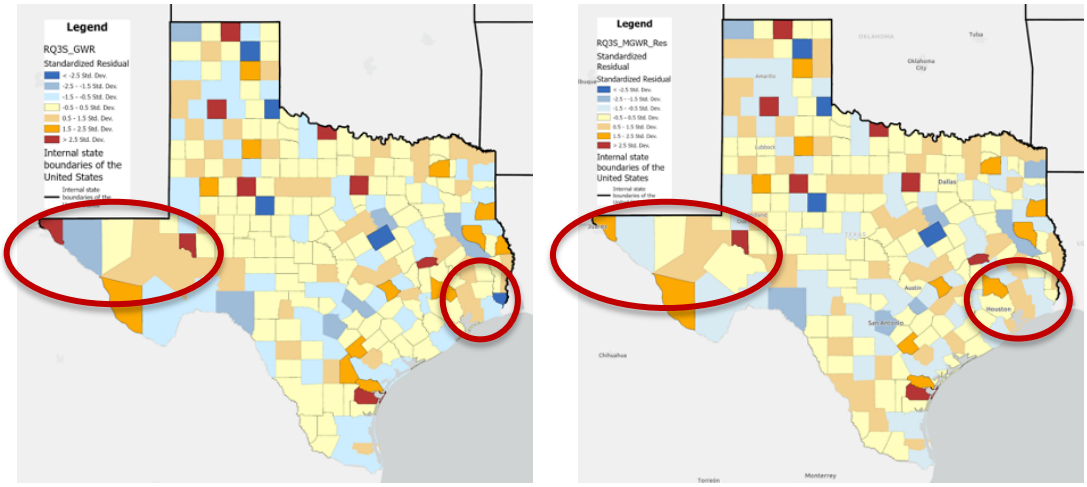
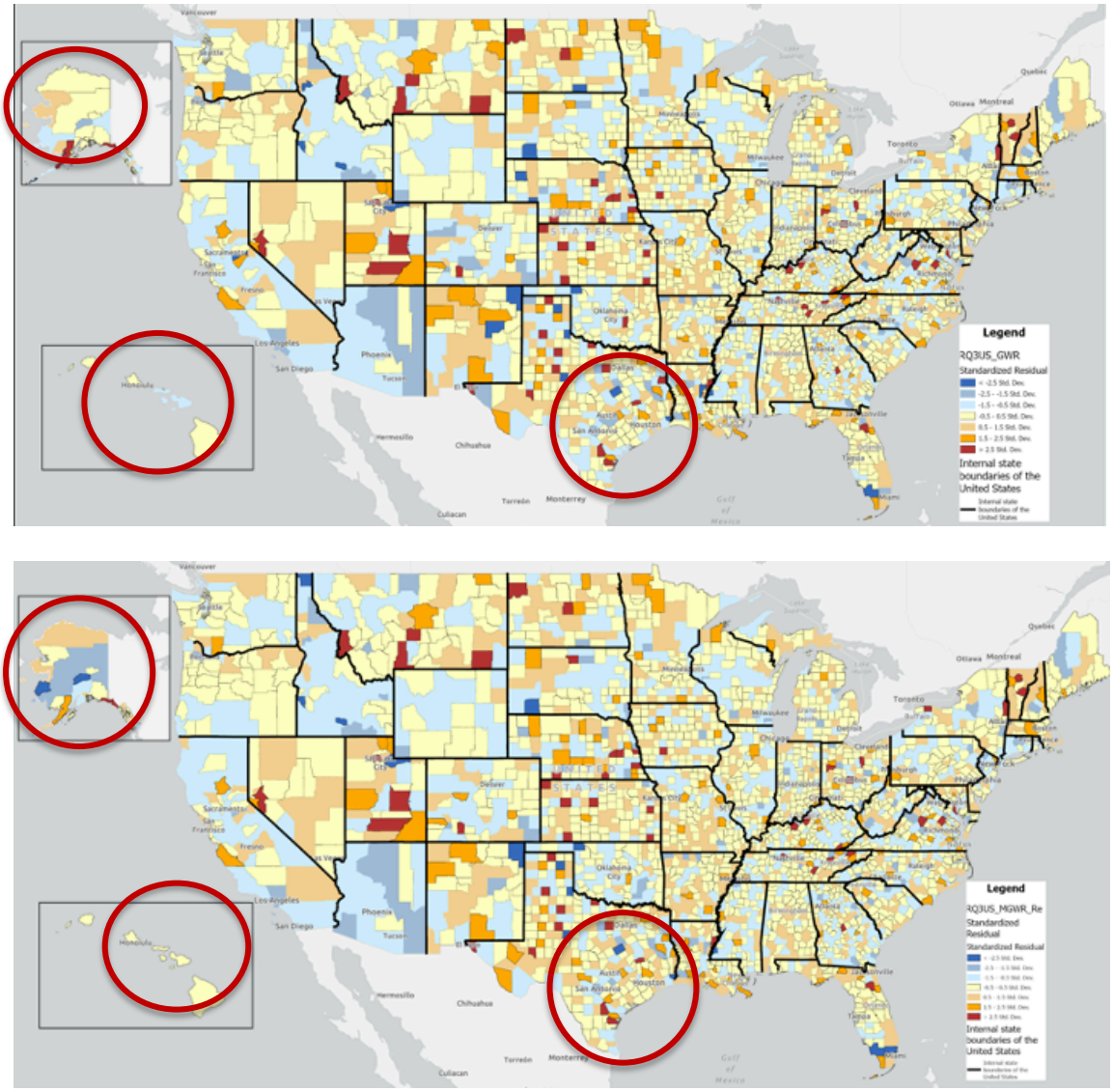


Figure 97 shows the GWR (A) compared to MGWR (B) depicting subtle differences (i.e., Alaska, Hawaii, and Texas in red circles due to the greater accuracy of the MGWR model.

Figure 97

The GWR Model (A) Compared to the MGWR (B)



Hence, the above statistical and geospatial-statistical analyses, Table 30, and Appendix F, point to an MLR model as follows:

$$Y_{ADRD\_Prev} = \beta_o + \beta_{smokers}(Smokers_{\%}) + \beta_{FI}(FI_{\%}) + \beta_{SevereHousing}(SevereHousingProblems_{\%}) + \beta_{Uninsured\_Adults}(Uninsured\ Adults_{\%}) + \beta_{HCCosts}(HC_{Costs}) + \beta_{Blacks}(Blacks_{\%}) + \beta_{AIAN}(AIAN_{\%}) + \beta_{FEM4564}(FEM_{45064\%}) + \beta_{<65AH\%}(AH_{<65\%}) + \beta_{>65AH\%}(AH_{>65\%})$$

$$Y_{ADRD\_Prev} = 3.70 - 0.48(Smoker\%) + 0.72(Food\ Insecure\%) - 0.028(SevereHousingProblems_{\%}) + 0.057(Uninsured\ Adults_{\%}) + 0.0001(HC_{Costs}) - 0.011(Blacks_{\%}) - 0.021(AIAN_{\%}) - 9.30(FEM_{45064\%}) + 0.015(AH_{<65\%}) + 0.086(AH_{>65\%})$$

Research Question 4

RQ4: Is there a statistically significant predictable relationship exist between SDoH (education attainment, income, housing, and pollution) and the prevalence of ADRD in the U.S. context of T2DM and AH?

$H_0$4: No, there is no statistically significant predictable relationship between SDoH (education attainment, income, housing, and pollution) and the prevalence of ADRD in the U.S. context of T2DM and AH.

H_a4: Yes, there is a statistically significant predictable relationship between SDoH (education attainment, income, housing, and pollution) and the prevalence of ADRD in the U.S. context of T2DM and AH.

The required MLR analysis in SPSS v. 29, after controlling for age, gender, and ethnicity, to answer this question, revealed a statistically significant predictable relationship between ADRD prevalence in the general population where the influence of SDoH, behaves in linear model equivalent to Y= 9.97 + 0.173X, F(1, 35) = 71.674, *p*

< .001 with an R^2 = 0.447, and *adj*-R^2 = 0.441, could explain up to 44.7% of related ADRD prevalence (see Table 33–36 and Figure 98). at a 95%CI and an effect size $f^2 = R^2/(1-R^2)$ = 0.808 which rendered a statistical power ($1-\beta$) ~99.99% calculated post-hoc. These results reject the null hypothesis in favor of the alternative.

Table 33 shows the Descriptive statistics of the variables evaluated in the ADRD-SDoH in the US context of T2DM and Arterial Hypertension (AH) prevalence, including Osteoporosis and Schizophrenia (SZ) and other psychotic disorders prevalence MLR model via SPSS v.29 at 95%CI.

Table 33

Descriptive Statistics of the Variables in the MLR Model for the ADRD-SDoH in the US Context of T2DM and Hypertension Prevalence (Including Osteoporosis and Schizophrenia (SZ) and Other Psychotic Disorders Prevalence)

Descriptive Statistics

	Mean	Std. Deviation	N
ADRD Prevalence Total Population	9.965120	2.5948589	3142
Population Percent Smokers	17.8726	3.66004	3142
Population Percent Obese	31.474	4.5141	3142
Food Environment Index	7.364	1.3148	3142
Population Percent Food Insecure	14.139	4.2360	3142
Population Percent at 20th Percentile Income	20897.95	6230.447	3142
Income Ratio /Income Inequality	4.520	.7442	3142
Chlamydia Infection Rate	345.096	248.4230	3142
Percent of Cohort Graduating from High School	73.3014	31.66884	3142
Percen Population 25-44 with Some College	57.2305	11.55042	3142
Percent Population with Severe Housing Problems	14.4618	4.78948	3142
Age-Adjusted Mortality	393.015	122.6784	3142
Percent Adults Uninsured	14.2840	6.25362	3142
Health Care Costs	9608.72	1566.086	3142
Median Household Income	49506.35	12915.510	3142
Air_Pollution_PM25	8.855	1.8269	3142
Population Percent Rural	58.4515	31.56833	3142
County Health Behaviors Rank	46.76	41.715	3142
County Health Outcomes Rank	46.76	41.715	3142
Population Percent African-American (non-Hispanic Black)	8.9425	14.31113	3142
Population Percent American Indian / Alaskan Native (AIAN)	2.3094	7.72066	3142
Population Percent Asian	1.4856	2.85933	3142
Population Percent Native Hawaiian & Other Pacific Islander	.1349	.98500	3142
Population Percent Hispanic/Latino	9.2896	13.66175	3142
County Female Population Percentage 18-24	.0406	.01656	3142
County Female Population Percentage 25-44	.1135	.01606	3142
County Female Population Percentage 45-64	.1332	.01446	3142
County Female Population Percentage >65	.1038	.02393	3142
T2DM Prevalence Population <65	24.8078	8.24493	3142
T2DM Prevalence Population >65	25.5013	8.38433	3142
Hypertension Prevalence Population <65	40.863915	12.8963573	3142
Hypertension Prevalence Population >65	57.057662	15.6214096	3142
Osteoporosis Prevalence Population <65	1.3969	1.38472	3142
Osteoporosis Prevalence Population >65	3.9335	3.47369	3142
Schizophrenia & Other Psychotic Disorders Prevalence Population <65	6.8308	4.45230	3142
Schizophrenia & Other Psychotic Disorders Prevalence Population >65	1.2955	.93668	3142

Table 34 shows the MLR model summary of the ADRD-SDoH in the US Context of T2DM and Arterial Hypertension (AH) prevalence relationships, which includes

Osteoporosis (OP) and Schizophrenia (SZ) and Other Psychotic Disorders prevalence.

Table 34

MLR Model Summary of the ADRD-SDoH in the US Context of T2DM and Hypertension Including Osteoporosis and Schizophrenia and Other Psychotic Disorders Prevalence

Model Summary[b]

					Change Statistics					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.668[a]	.447	.441	1.9408352	.447	71.674	35	3106	<.001	1.690

a. Predictors: (Constant), Schizophrenia & Other Psychotic Disorders Prevalence Population >65, Population Percent Rural, Population Percent Native Hawaiian & Other Pacific Islander, County Health Behaviors Rank, Population Percent American Indian / Alaskan Native (AIAN), Osteoporosis Prevalence Population <65, Income Ratio /Income Inequality, Population Percent Hispanic/Latino, Health Care Costs, County Female Population Percentage 18-24, T2DM Prevalence Population <65, Percent of Cohort Graduating from High School, Population Percent Asian , Food Environment Index, Population Percent Obese, County Female Population Percentage 25-44, County Female Population Percentage 45-64, Population Percent African-American (non-Hispanic Black), Air_Pollution_PM25, Schizophrenia & Other Psychotic Disorders Prevalence Population <65, Percent Population with Severe Housing Problems, Age-Adjusted Mortality, Percent Adults Uninsured, Percen Population 25-44 with Some College, Chlamydia Infection Rate, Hypertension Prevalence Population >65, Population Percent Smokers, County Female Population Percentage >65, Osteoporosis Prevalence Population >65, County Health Outcomes Rank, Median Household Income, Population Percent Food Insecure, T2DM Prevalence Population >65, Hypertension Prevalence Population <65, Population Percent at 20th Percentile Income

b. Dependent Variable: ADRD Prevalence Total Population

Table 35

The β-Coefficients for MLR Model Addressing Research Question 4

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients			Correlations			Collinearity Statistics	
Model		B	Std. Error	Beta	t	Sig.	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	5.158	1.225		4.211	<.001					
	Population Percent Smokers	-.054	.019	-.076	-2.878	.004	.004	-.052	-.038	.253	3.950
	Population Percent Obese	.000	.012	-.001	-.039	.969	.059	-.001	-.001	.429	2.329
	Food Environment Index	.042	.039	.022	1.077	.282	-.056	.019	.014	.446	2.243
	Population Percent Food Insecure	.062	.020	.101	3.172	.002	.107	.057	.042	.176	5.692
	Population Percent at 20th Percentile Income	-8.812E-6	.000	-.021	-.401	.688	-.088	-.007	-.005	.064	15.624
	Income Ratio /Income Inequality	-.081	.086	-.023	-.953	.341	.064	-.017	-.013	.296	3.379
	Chlamydia Infection Rate	.000	.000	.016	.670	.503	.042	.012	.009	.307	3.263
	Percent of Cohort Graduating from High School	-.001	.001	-.016	-.942	.347	.061	-.017	-.013	.599	1.670
	Percen Population 25-44 with Some College	.007	.006	.031	1.246	.213	-.096	.022	.017	.295	3.386
	Percent Population with Severe Housing Problems	-.025	.011	-.047	-2.272	.023	-.031	-.041	-.030	.418	2.391
	Age-Adjusted Mortality	-.001	.001	-.045	-1.871	.061	.079	-.034	-.025	.309	3.238
	Percent Adults Uninsured	.054	.009	.129	5.869	<.001	.179	.105	.078	.368	2.720
	Health Care Costs	.000	.000	.083	4.847	<.001	.181	.087	.065	.613	1.630
	Median Household Income	1.100E-5	.000	.055	1.118	.264	-.081	.020	.015	.074	13.464
	Air_Pollution_PM25	-.053	.028	-.038	-1.928	.054	.069	-.035	-.026	.468	2.137
	Population Percent Rural	-.003	.002	-.031	-1.444	.149	.002	-.026	-.019	.389	2.568
	County Health Behaviors Rank	.000	.002	-.005	-.206	.837	.120	-.004	-.003	.254	3.931
	County Health Outcomes Rank	.003	.002	.056	2.051	.040	.130	.037	.027	.242	4.129
	Population Percent African-American (non-Hispanic Black)	-.011	.005	-.059	-2.333	.020	.105	-.042	-.031	.278	3.597
	Population Percent American Indian / Alaskan Native (AIAN)	-.015	.008	-.045	-2.025	.043	-.095	-.036	-.027	.355	2.820
	Population Percent Asian	-.023	.016	-.026	-1.444	.149	-.052	-.026	-.019	.556	1.797
	Population Percent Native Hawaiian & Other Pacific Islander	.041	.039	.015	1.033	.302	.010	.019	.014	.799	1.251
	Population Percent Hispanic/Latino	.004	.004	.020	.882	.378	.091	.016	.012	.334	2.993
	County Female Population Percentage 18-24	-4.104	3.106	-.026	-1.321	.186	.003	-.024	-.018	.453	2.206
	County Female Population Percentage 25-44	-4.273	3.939	-.026	-1.085	.278	.025	-.019	-.014	.300	3.337
	County Female Population Percentage 45-64	-10.250	3.678	-.057	-2.787	.005	-.058	-.050	-.037	.424	2.358
	County Female Population Percentage >65	1.351	3.108	.012	.435	.664	.002	.008	.006	.217	4.614
	T2DM Prevalence Population <65	.045	.011	.143	4.072	<.001	.503	.073	.054	.144	6.961
	T2DM Prevalence Population >65	-.051	.012	-.165	-4.165	<.001	.516	-.075	-.056	.113	8.827
	Hypertension Prevalence Population <65	-.007	.008	-.035	-.827	.409	.569	-.015	-.011	.101	9.926
	Hypertension Prevalence Population >65	.087	.007	.523	11.749	<.001	.591	.206	.157	.090	11.112
	Osteoporosis Prevalence Population <65	-.269	.049	-.144	-5.449	<.001	.190	-.097	-.073	.256	3.902
	Osteoporosis Prevalence Population >65	.130	.020	.174	6.635	<.001	.231	.118	.089	.258	3.871
	Schizophrenia & Other Psychotic Disorders Prevalence Population <65	-.026	.012	-.045	-2.248	.025	.313	-.040	-.030	.438	2.282
	Schizophrenia & Other Psychotic Disorders Prevalence Population >65	.735	.061	.265	12.107	<.001	.476	.212	.162	.371	2.694

a. Dependent Variable: ADRD Prevalence Total Population

As the null hypothesis is rejected in favor of the alternative, it is worth mentioning that some of the variables did not render a statistically significant contribution to the model's outcome ADRD prevalence (i.e., percentage of obese, FEI, 20^{th} percentile income, income ratio, chlamydia rate, percentage of rural population, age-adjusted mortality, adults 25–44 with incomplete postsecondary education, HS graduation rate, percentage of severe housing problems, air pollution, county's health behaviors and outcomes ranks). Population percentages by race/ethnicity showed that, compared to non-Hispanic Whites, only non-Hispanic Blacks and AIAN showed a statistically significant and inverse relationship to the outcome (ADRD prevalence). Regarding age and gender, only women aged 45–64 showed a statistically significant ($p <$ .007), yet inverse, relationship to ADRD prevalence compared to females under 18.

Table 36 shows the residual statistics of the MLR model for the ADRD-SDoH in the US context of T2DM and Arterial Hypertension (AH) prevalence relationships, which includes Osteoporosis (OP) and Schizophrenia (SZ) and Other Psychotic Disorders prevalence relationships addressing Research Question 4 show the statistics as used in the scatter plot of Figure 85.

Table 36

The Residual Statistics of the MLR Model for the ADRD-SDoH in the US Context of T2DM and Hypertension Prevalence Addressing Research Question 4

Residuals Statistics[a]

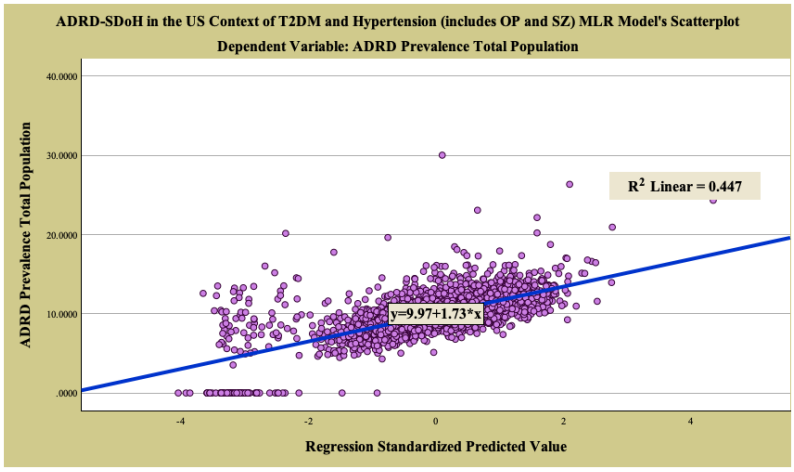
	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	2.961971	17.507500	9.965120	1.7344813	3142
Residual	-8.3696175	19.8933334	.0000000	1.9299916	3142
Std. Predicted Value	-4.038	4.348	.000	1.000	3142
Std. Residual	-4.312	10.250	.000	.994	3142

a. Dependent Variable: ADRD Prevalence Total Population

Figure 98 shows the MLR Model Plot for the ADRD Prevalence associated with SDoH in the US Context of T2DM and Arterial Hypertension (AH) prevalence, which includes Osteoporosis (OP), Schizophrenia (SZ), and Other Psychotic Disorders prevalence addressing Research Question 4.

Figure 98

MLR Model Plot for the ADRD Prevalence Associated with SDoH in the US Context of T2DM and Hypertension Prevalence Addressing Research Question 4



The GWR and MGWR statistical analysis, using ASU's MGWR 2.2.1, revealed the following refined result to the above MLR analysis:

Table 37

Model Summary for the OLS, GWR, and MGWR Analysis of the ADRD Prevalence Associated with SDoH in the US Context of T2DM and Hypertension Prevalence Addressing Research Question 4

	GWR Model		MGWR Model	
ADRD Prevalence	**OLS**	**GWR**	**OLS**	**MGWR**
Adj. R^2	0.418	**0.486**	0.418	**0.575**
ACIc	6323.114	6208.249	6323.114	5821.164

The MGWR analysis renders a more accurate model at the global and local scales with an AICc= 5821.164 and *adj.* R^2 = 0.575 where the influence of SDoH and T2DM prevalence could explained up to 57.5% of related ADRD prevalence. These effects are better observed in Figures 99 and 100.

Figure 99 shows the GWR (top) compared to MGWR (bottom) depicting subtle differences (i.e., Alaska, Hawaii, and Texas in red circles due to the greater accuracy of the MGWR model.

Figure 99

The GWR Model (top) Compared to MGWR (bottom)

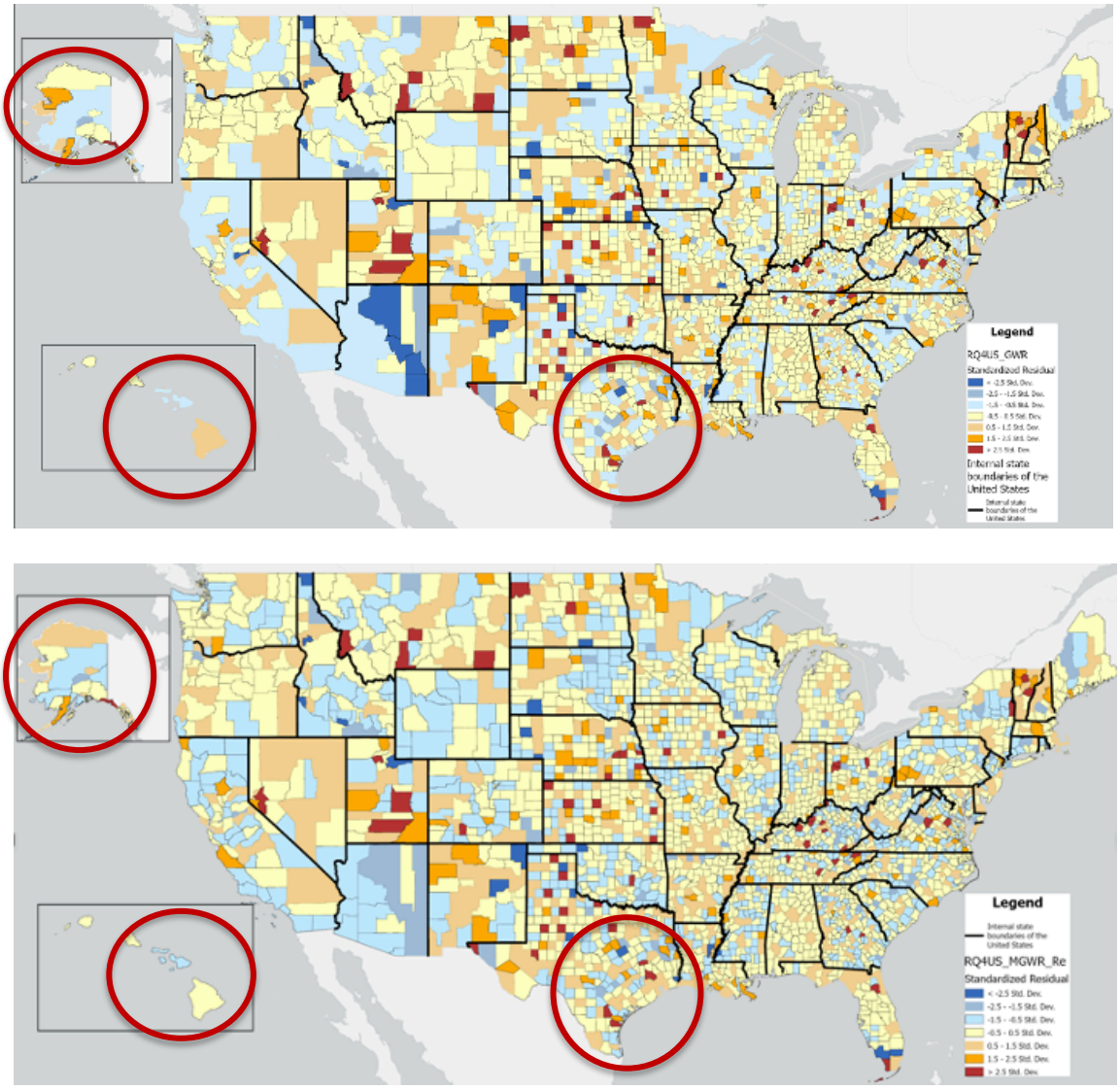
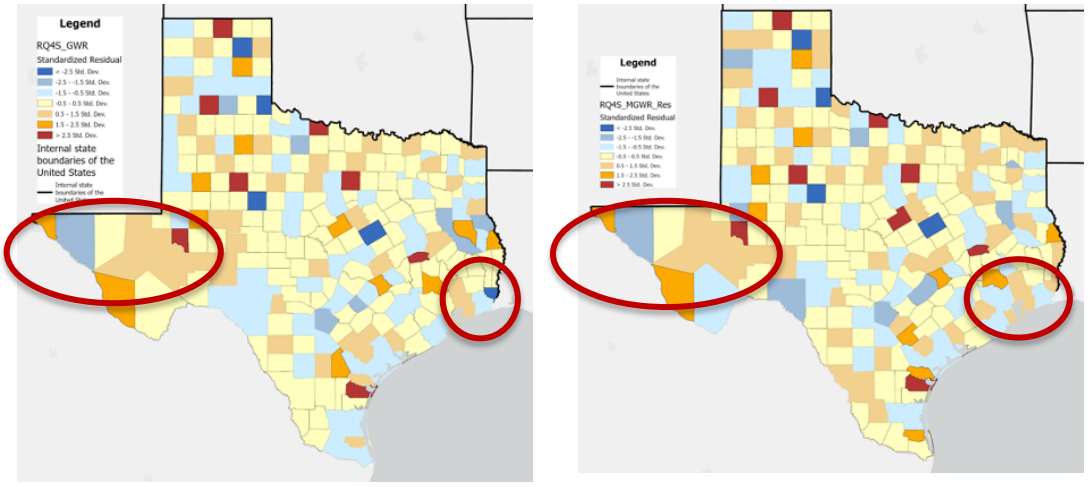


Figure 100 shows that at the local context level, the MGWR model (right) is more accurate than the GWR (left). The red circles show how areas of Texas, previously (GWR) assessed with lower ADRD prevalence, are brought to consideration via the MGWR model (right).

Figure 100

The GWR Model Compared to the MGWR in the Local Context).



At the local context level, the MGWR model (right) is more accurate than the GWR (left). The red circles show how areas of Texas, previously (GWR) assessed with lower ADRD prevalence, are brought to consideration via the MGWR model (right).

Hence, the above statistical and geospatial-statistical analyses, Table 35, and Appendix G, point to an MLR model as follows:

$$Y_{ADRD\_Prev} = \beta_o + \beta_{smokers}\,(Smokers_{\%}) + \beta_{FI}(FI_{\%}) + \beta_{SevereHousing}(SevereHousingProblems_{\%}) + \beta_{Uninsured\_Adults}(Uninsured\ Adults_{\%}) + \beta_{HCCosts}\,(HC_{Costs}) + \beta_{HORank}(HO_{Rank}) \beta_{Blacks}\,(Blacks_{\%}) + \beta_{AIAN}\,(AIAN_{\%}) + \beta_{FEM4564}(FEM_{45064\%}) + \beta_{<65AH\%}(AH_{<65\%}) + \beta_{>65AH\%}(AH_{>65\%})$$

$$Y_{ADRD\_Prev} = 5.158 - 0.54(Smoker\%) + 0.62(Food\ Insecure\%) - 0.025(SevereHousingProblems_{\%}) + 0.054(Uninsured\ Adults_{\%}) + 0.0001(HC_{Costs}) + 0.003(HO_{Rank}) - 0.011\,(Blacks_{\%}) - 0.015\,(AIAN_{\%}) -$$

$10.25(FEM_{45064\%}) + 0.045(T2DM_{<65\%}) - 0.051(T2DM_{>65\%}) - 0.007(AH_{<65\%}) + 0.087(AH_{>65\%}) - 0.269(OP_{<65\%}) + 0.130(OP_{>65\%}) - 0.026(SZ_{<65\%}) + 0.735(SZ_{>65\%})$

Summary

This quantitative cross-sectional design evaluated the associations between ADRD prevalence and SDoH (educational attainment, income, housing, and environmental pollution) in the U.S. context of T2DM and AH. To assess these effects, I explored four RQs and their related null and alternative hypotheses. Regarding RQ1, at least one statistically significant predictable relationship exists between ADRD prevalence and contextually found SDoH (education, income, housing, and pollution) and behaves in a linear model equivalent to Y= 9.97 + 0.77X, $F(1,27) = 11.018$, $p < .001$ with an $R^2 = 0.087$, and $adj\text{-}R^2 = 0.079$, could explain up to 8.7% of related ADRD prevalence. Regarding RQ2, at least one statistically significant predictable relationship exists between ADRD prevalence and T2DM and behaves in a linear model equivalent to Y= 9.97 + 0.147X, $F(1, 29) = 51.212$, $p < .001$ with an $R^2 = 0.323$, and $adj\text{-}R^2 = 0.317$, could explain up to 32.3% of related ADRD prevalence. Regarding RQ3, at least one statistically significant predictable relationship exists between ADRD prevalence and AH and behaves in a linear model equivalent to Y= 9.97 + 0.164X, $F(1, 29) = 71.972$, $p < .001$ with an $R^2 = 0.401$, and $adj\text{-}R^2 = 0.396$, could explain up to 40.1% of ADRD prevalence. Last, regarding RQ4, At least one statistically significant predictable relationship exists between ADRD prevalence and AH and behaves in a linear model

equivalent to Y= 9.97 + 0.173X, $F(1, 35) = 71.674$, $p < .001$ with an $R^2 = 0.447$, and *adj-*$R^2 = 0.441$, could explain up to 44.7% of related ADRD prevalence.

The statistically significant predictable relationships found could help explain the relationships between ADRD prevalence and SDoH in the U.S. context of T2DM and AH.

Chapter 5 will focus on the discussion of such relevant findings and their meaningfulness to public health practice and related people's well-being in a sustainable approach to positive social change that catalyzes human development with economic growth, empowering women from within the community.

Chapter 5: Discussion, Conclusions, and Recommendations

Introduction

The purpose of this quantitative cross-sectional study was to evaluate the association between ADRD prevalence (dependent variable) and SDoH (educational attainment, income, housing, and pollution) in the U.S. context of T2DM and AH (as predictor variables). For this analysis, I examined health and sociodemographic information at the U.S. county level (the unit of analysis) from the 2018 U.S. CHR&R (CHR&R, 2023) and the CMS multiple chronic diseases (CMS, 2018) secondary data sets. I used GIS-software (ArcGIS Online and ArcGIS Pro 3.2) to prepare the data (coded by county) for geospatial and statistical evaluation at 95% CI, $p < .05$.

ADRD prevalence, the dependent outcome variable, was numerically continuous at the interval/ratio level of measurement. The independent predictor variables in the SDoH-related domains (educational attainment, income, housing, and pollution) were also numerically continuous at the interval/ratio level of measurement. To evaluate these relationships, I used geospatial statistics and statistical analyses that included MLR via SPSS v.29, GIS smart-mapping technology, and related GWR and MGWR via ArcGIS Online, ArcGIS Pro 3.2 from the Environmental Systems Research Institute, and the ASU School of Geographical Science and Urban Planning's MGWR 2.2.1 software.

In this quantitative cross-sectional study, I addressed the first four gaps identified in the current literature regarding the association between ADRD prevalence, development, onset, and SDoH (educational attainment, income, housing, and pollution) in the U.S. context of T2DM and AH. These gaps include the influence of SDoH on the

prevalence of ADRD, the geotemporal relationship effects of exposures (SDoH and related environmental pollution) and ADRD prevalence in the U.S. context of chronic disease, the influence of chronic disease (i.e., T2DM, AH, and related CVD comorbidities) on the development and onset of ADRD, an early detection or warning diagnosing system that could predict or point to the early modifiable risk factors for the prevalence, development, and onset of ADRD at the population and individual levels, and the perimenopausal and menopausal-related hormonal treatment timing effects on the development and onset of ADRD. I did not address the last item in this study.

Interpretation of the Findings

The smart-mapping technique by relationships revealed three significant findings in the general population and their living area. First, a convergence of SDoH disproportionately affected the Southern and Southeastern parts of the United States. A similar effect was observed in U.S. rural areas and in areas historically inhabited by lower income demographics and related economic minorities (i.e., AIAN, non-Hispanic Blacks, and Latinos). Second, ADRD, T2DM, AH, and related OP and SZ prevalence were higher and converging in those areas and populations. Third, the areas and populations identified in the first two findings correlated to areas of higher income inequality compared to the national mean. Smart mapping by relationship, GWR, and MGWR analyses via Arc GIS Online and ArcGIS Pro revealed specific areas with the confluence of SDoH, disproportionate disease outcomes, and poverty related to income inequality, often affecting lower income demographics and related economic minorities. Per my understanding of the existing literature, this study provides new knowledge pertaining to

disease outcomes in the U.S. context of confluent SDoH and accompanying comorbidities.

This study's findings confirm the existing literature pointing to a disproportionate disease burden on lower income demographics and related economic minorities (Bhunia & Shit, 2019, CDC, 2022; Mielke, 2018). The authors of these studies evaluated related SDoH separately, not concurrently, and not in their spatiotemporal context. This study's findings contextually depict the spatiotemporal confluence of SDoH, chronic comorbidities, and disease outcome, which, in the context of lower income and other vulnerable demographics, could point to the genesis of a disease-poverty conundrum affecting current and future generations in those areas, with at least socioeconomic, if not economic, repercussion to the United States. In this dissertation's the grounding SDoH framework proves its validity and alignment encompassing the HBM, SEM, and PoD model, all which have contributed to the herein developed and proposed systems engineering approach to a concept of sustainable positive social change in a circular economy.

The MLR/OLS, GWR, and MGWR statistical and geo-statistical analyses in this study revealed several things. Regarding ADRD prevalence and SDoH addressed in RQ1, contextually found SDoH affecting the general population, under and over 65 years of age, proved to be statistically significant predictors of ADRD prevalence. The population percentages of smokers, food insecure, uninsured adults, AIAN, Hawaiians and other Pacific Islanders, non-Hispanic Black, and women aged 45–64 along with chlamydia infection rate, household health care costs, MHI, and air pollution were found to be the

most significant predictors and contributing variables to predict ADRD prevalence. This analysis and approach are original and novel, for neither these determinants nor their contextual relationships have been previously evaluated concurrently and in association with ADRD prevalence, development, or onset, according to my review of the literature. Moreover, this analysis and results seem to point to the development of an early warning or predictor system for ADRD or similar pathophysiology in association with contextual SDoH.

Concerning ADRD and T2DM prevalence, addressed in RQ2, T2DM prevalence was found to be a statistically significant predictor of ADRD prevalence. Similarly, the population percentage of older adults was positive and statistically significant for smokers, food insecure, uninsured, AIAN, non-Hispanic Black, and women aged 45–64, along with increased household health care costs and high T2DM prevalence for people over and under 65 years of age. These factors were the most significant predictors and contributing variables for ADRD prevalence. Neither T2DM nor these determinants, or their contextual relationships, have been previously evaluated concurrently and in association with ADRD prevalence, development, or onset, according to my review of the literature. Moreover, this analysis and results seem to point to the development of an early warning or predictor system for ADRD or similar pathophysiology in association with T2DM and contextual SDoH.

Regarding ADRD and AH prevalence, addressed in RQ3, AH proved to be a statistically significant predictor of ADRD prevalence. The population percentages of smokers, food insecure, with severe housing problems, uninsured adults, AIAN, non-

Hispanic Black, and females 45-64, along with household health care costs and AH prevalence for people over and under 65 years of age, were found to be the most significant predictors and contributing variables to predict ADRD prevalence. Neither AH nor these determinants, or their contextual relationships, have been previously evaluated concurrently and in association with ADRD prevalence, development, or onset. Moreover, this analysis and results seem to point to the development of an early warning or predictor system for ADRD or similar pathophysiology in association with AH and contextual SDoH.

Concerning ADRD prevalence and SDoH in the U.S. context of T2DM and AH, addressed in RQ4, T2DM, AH, and the often-accompanying comorbidities OP, SZ, and other psychotic disorders proved to be statistically significant predictors of ADRD prevalence. The population percentages of smokers, food insecure, with severe housing problems, uninsured adults, AIAN, non-Hispanic Black, and females 45-64 along with household health care costs, air pollution, county's health outcome rank, T2DM, OP, SZ and other psychotic disorder prevalence for people over and under 65 years of age, and AH prevalence for people >65, were found to be the most significant predictors and contributing variables to predict ADRD prevalence. This analysis and approach are original and novel, for neither the confluence of T2DM and AH nor these determinants, nor their contextual relationships, have been previously evaluated concurrently and in association with ADRD prevalence, development, or onset. Moreover, this analysis and results seem to point to the development of an early warning or predictor system for ADRD or similar pathophysiology in association with T2DM, AH, and contextual SDoH.

Pondering that the SDoH entail all nonmedical factors affecting health dynamics and related outcomes, thus including the socio-political settings in which people are born, grow, work, live, and age, alongside the natural and built environment and the socioeconomics and social-political constructs that shape and condition daily life (CDC, 2022). In comparison to previous research, this study also pointed to SDoH as statistically significant predictors of disease outcomes.

Moreover, this study validated its proposed rationale that in an open market economy as that of the United States, access to and quality of health care depends on the status and level of employment, often determined by educational attainment and sheltered by the physical and financial security of home ownership, all directly and indirectly affected by the ecotoxicity of environmental pollution affecting the natural and built environment in a geo-temporal relationship that can be evaluated through the five domains of the SDoH framework.

The above statistical and geostatistical significant results from the four RQs find meaningfulness in their results. SDoH proved to be excellent statistical predictors of disease outcome. The geospatial and spatiotemporal contextual evaluation of disease outcome and related SDoH revealed a more robust effect size and model fit, which increases statistical power even for small sample sizes. The MGWR model provides a more robust statistical model, especially locally. This characteristic allows for a more accurate contextual evaluation of SDoH and Disease outcomes. It provides a physical sense to the resources-need allocation, which should integrate the community's perspective in the specific intervention strategy.

To these effects, the geo-temporal, and related geostatistical analyses via GWR and MGWR provide robust, more significant, and more accurate analyses of SDoH as geo-temporally varying relationships governing human health dynamics and related outcomes, disproportionately affecting lower income demographics, related economic minorities, and other vulnerable populations, especially in the U.S. context of chronic diseases. As such, the herein-evaluated relationship between disease outcome (ADRD prevalence), resulting from its development and onset in the U.S. context of protracted exposures to SDoH and the often-accompanying chronic comorbidities, is a replicable approach elsewhere. This statement is validated by the geospatial contextual statistical evaluation of outcome-predictor relationships accounting for SDoH as spatiotemporal varying relationships.

Limitations of the Study

While there were limitations to the study related to its cross-sectional design (Wang & Cheng, 2020) and secondary data analyses. The limitation imposed by secondary data wax related to the availability of data as the variables had been predetermined by CH&R and CMS. However, this study's analyses find asset in reporting and interpreting inferential associations and their related strengths, no causation. To these effects, GWR and MGWR strengthen the statistical analyses results (Charlton et al., 2009; Fotheringham et al., 2017; 2023) often found through bivariate and multivariate statistical analyses. Moreover, the use of GWR and its refinement MGWR reduce threats to validity and reliability while increasing the trustworthiness and generalizability of the proposed statistical models.

Furthermore, while five significant gaps, believed to influence the prevalence, development, and onset of ADRD, were identified, in the available scientific literature, based on the available data, only four of the five gaps were addressed through this study. These gaps included the influence of SDoH on the prevalence of ADRD in the population and its development and onset at the individual levels, the geo-temporal relationship effects of exposures (SDoH and related environmental pollution), and ADRD in the U.S. context of chronic disease, the influence of chronic disease (i.e., T2DM, AH, and related CVD comorbidities) on the development and onset of ADRD, an early detection or warning diagnosing system that could predict or point to the early modifiable risk factors for the prevalence, development and onset of ADRD at the population and individual levels, and perimenopausal and menopausal-related hormonal treatment timing effects on the development and onset of ADRD. This latter gap was not addressed through this study. However, the finding that the population percentage of women 45–64 was statistically significant and contributing to the ADRD prevalence model, although in an inverse relationship, could point to a new avenue of research related to the perimenopausal and menopausal-related hormonal treatment timing effects on the development and onset of ADRD. This is because of their age bracket and the statistical (inverse) relationship that points to a reduction of ADRD as the percentage of the female population aged 45–64 increases from the median.

Recommendations

While recognizing the scholarly contributions of this study, its design and statistical methods, specifically to ADRD prevalence associated with SDoH in the U.S.

context of T2DM and AH, further research is required to help understand the association between the prevalence, development, and onset of ADRD associated with the perimenopausal and menopausal-related hormonal treatment timing effects. It is also imperative to gain a better understanding of the seemingly protective effect of educational attainment over the prevalence, development, and onset of ADRD in the context of SDoH. It was not clear from the literature nor these analyses whether the timing or age of the highest educational attainment played a significant factor in delaying or preventing the development and onset of ADRD.

On the other hand, the novel study strategy, framework, and related geospatial statistical analyses provide the path for a statistically robust early warning or predictor system for ADRD prevalence associated with contextually found SDoH and chronic comorbidities. Perhaps, further research could exploit the potential of this dissertation to expand such analyses to the development and onset of ADRD associated with SDoH and menopausal related hormonal treatment timing and types. To these effects, the GWR and MGWR statistical analyses could render a robust statistical analyses method.

Furthermore, the lingering question regarding to whether other diseases can be evaluated and predicted based of contextual SDoH, finds herein a feasible approach to attempt to answer it.

Implications

This study put forth a circular economy approach to the system of systems engineering model that should drive positive social change in a sustainable approach. Empowering women in communities will help catalyze a sustainable approach to positive

social change, reinvesting in the community's social, economic, and natural resources through a circular economy model. This approach aims to promote human development with related economic growth, community belongingness, and ownership of their contextual problems through the empowerment of women, considered recognized as the fundamental pillar of the family, the unit cell of society, and the critical bridge for the ongoing generational gap between the young and the elderly.

To these effects, the SDoH framework grounding this study is validated and verified through this dissertation's approach and analyses that the SDoH framework intertwines traits of the HBM, SEM, and POD model, all of which have contributed to the herein developed and proposed systems engineering approach to a concept of sustainable positive social change in a circular economy approach. As such, public health strategies and public policy aimed to promote such human development through education, awareness, and empowerment would have a beginning and end on younger and more informed generations catalyzing better and equal access to education and health care, housing, natural and built environment, critical aspects of the U.S. Constitutional right of the pursuit of happiness.

This study's approach and related findings regarding ADRD prevalence and SDoH in the U.S. context of T2DM and AH confirm the existence of statistically significant predictable and, therefore, optimizable relationships about the prevalence, development, and onset of ADRD. These predictable relationships help justify, develop, and implement new public health strategies based on community-based participatory research to learn, understand, and engage the contextual factors influencing the

community regarding their health dynamics and related outcomes. Moreover, these findings lend creed to the above-proposed systems-of-systems perspective to sustainable positive social change. Furthermore, this study's approach and findings point to the validity of the claim that, as in the POD model (Benet, 2013), the local spatiotemporal contextual varying relationships (i.e., SDoH and polarities' pairs) behave in a predictable and optimizable spatiotemporal relationship for which GWR and MGWR renders a robust statistical method and evaluation tool.

Conclusion

As our generation observes the passing of our elders' generation and the upbringing of the youngest, the old colloquial saying still resonates: "A mind is a terrible thing to waste." We often hear and think of "children as the future of society."

However, what future can we speak of if we do not care for and cultivate our children's mental and physical well-being now? Should we not focus on breaking free of the seemingly endless disease-poverty conundrum that SDoH contextually imposes on society and disproportionately on lower-income demographics, related economic minorities, and other vulnerable populations, especially in the US context of chronic disease? Such seems to reflect a future for our society if we do not address the burdens imposed by contextual SDoH and their associated political and commercial determinants. Empowerment through human development and related economic growth provides a meaningful solution to most of these problems, especially in a globalized market economy. Empowering communities through education and economic development in their contextual setting and a sustainable approach could provide for better and equal

access to educational and healthcare infrastructure and services from younger ages, allowing these communities a fair chance for their development and political and economic independence. Is this the elusive healthcare for all of Alma Atta and the reimagined by Marmot (205), Farmer et al. (2013), and Dawes (2020)?

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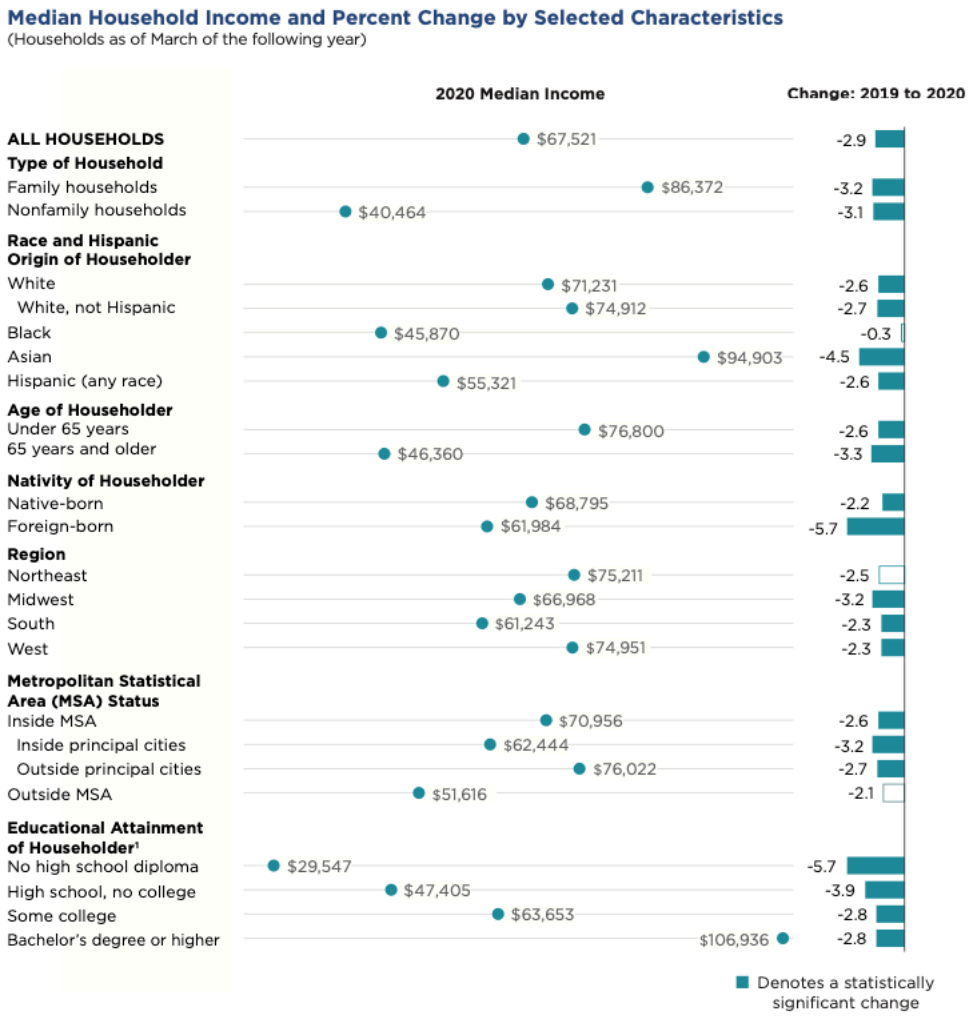
Appendix A: 2020 US Median Household Income and Percentage Change by Selected Characteristics

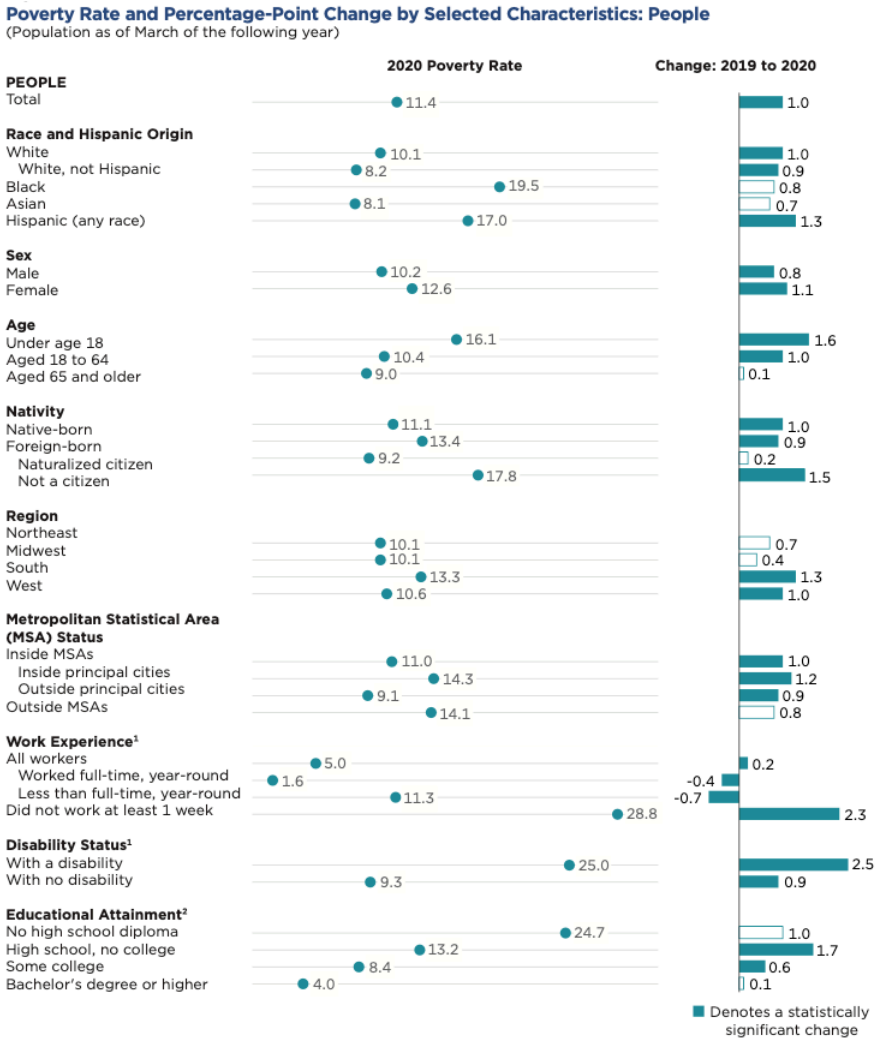


Note. Statistically significant indicates the change is statistically different from 0 at the 90% confidence level. Margins of error and other related estimates are available in Table A-1. Information on confidentiality protection, sampling error, nonsampling error, and definitions is available at the U.S. Census Bureau's website (https://www2.census.gov/programs-surveys/cps/techdocs/cpsmar21.pdf). From U.S.

Census Bureau, Current Population Survey, 2020 and 2021 Annual Social and Economic Supplements (CPS ASEC). In the public domain.

[a] Householders aged 25 and older. In 2020, the median household income for this group was $57,317.

Appendix B: 2020 US Poverty Rate and Percentage-Point Change by Selected Characteristics: People



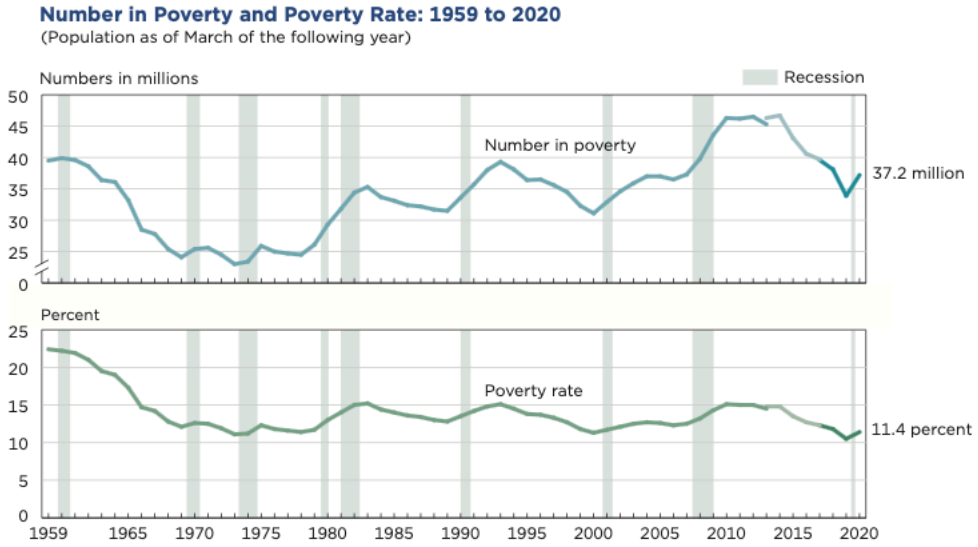
1. Population limited to individuals aged 18 to 64. The overall poverty rate for this group in 2020 was 10.4 percent.

2. Population limited to individuals aged 25 and older. In 2020, the overall poverty rate for this group was 9.5 percent.

Notes: Statistically significant indicates that the change is significantly different from zero at the 90 percent confidence level. Margins of error and other related

estimates are available in Table B-1. Information on confidentiality protection, sampling error, nonsampling error, and definitions is available at <https://www2.census.gov/programs-surveys/cps/techdocs/cpsmar21.pdf). From US Census Bureau, Current Population Survey, 2020 and 2021 Annual Social and Economic Supplements (CPS ASEC). In the public domain.

Appendix C: US Poverty and Poverty Rate for 1959 to 2020



Notes: The data for 2017 and beyond reflect the implementation of an updated processing system. The data for 2013 and beyond reflect the implementation of the redesigned income questions. Refer to Table B-4 for historical footnotes. The data points are placed at the midpoints of the respective years. Information on recessions is available in Appendix A. Information on confidentiality protection, sampling error, nonsampling error, and definitions is available at <https://www2.census.gov/programs-surveys/cps/techdocs/cpsmar21.pdf). From US Census Bureau, Current Population Survey, 1960 to 2021 Annual Social and Economic Supplements (CPS ASEC). In the public domain.

Appendix D: Ordinary Least Squares, Geographically Weighted Regression, and Multiscale Geographically Weighted Regression for Research Question 1

Figure D1

Ordinary Least Squares Results for Research Question 1

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==========================================================================
MGWR Version: 2.2.1
Released on: 03/20/2020
Source code is available at: https://github.com/pysal/mgwr
Development Team: Ziqi Li, Taylor Oshan, Stewart Fotheringham, Wei Kang,
Levi Wolf, Hanchen Yu, Mehak Sachdeva, and Sarah Bardin
Spatial Analysis Research Center (SPARC)
Arizona State University, Tempe, USA
==========================================================================
Model type:                                                      Gaussian
Number of observations:                                              2735
Number of covariates:                                                  30
Dependent variable:                                              ADRDPrev
Variable standardization:                                              On
Total runtime:                                                   0:01:15

Global Regression Results
--------------------------------------------------------------------------
Residual sum of squares:                                        2498.176
Log-likelihood:                                                -3756.942
AIC:                                                            7573.883
AICc:                                                           7576.617
R2:                                                                0.087
Adj. R2:                                                           0.077

Variable                                   Est.         SE  t(Est/SE)    p-value
---------------------------------- ------------ ---------- ---------- ----------
Intercept                                -0.000      0.018     -0.000      1.000
PercentSmokers                           -0.088      0.037     -2.377      0.017
PercentObese                              0.020      0.030      0.667      0.505
FoodEnvironmentIndex                     -0.008      0.029     -0.282      0.778
PercentFoodInsecure                       0.084      0.045      1.843      0.065
@20thPercentileIncome                    -0.084      0.068     -1.233      0.218
IncomeRatio                              -0.019      0.034     -0.569      0.569
ChlamydiaRate                             0.030      0.033      0.895      0.371
GraduationRate                            0.031      0.024      1.261      0.207
PercentSomeCollege                       -0.007      0.034     -0.212      0.832
PercentSevereHousingProblems             -0.055      0.028     -1.948      0.051
AgeAdjustedMortality                      0.042      0.033      1.267      0.205
PercentAdultsUninsured                    0.191      0.031      6.134      0.000
HealthCareCosts                           0.089      0.024      3.754      0.000
HouseholdIncome                           0.154      0.063      2.441      0.015
5.1                                       0.040      0.028      1.425      0.154
PercentRural                              0.023      0.030      0.762      0.446
HealthBehaviorsRank                      -0.029      0.036     -0.794      0.427
HealthOutcomesRank                        0.034      0.037      0.939      0.348
PercentAfricanAmerican                   -0.508      0.260     -1.953      0.051
PercentAmericanIndianAlaskanNative       -0.379      0.151     -2.514      0.012
PercentAsian                             -0.153      0.062     -2.462      0.014
PercentNativeHawaiianOtherPacificIslander     -0.004      0.034     -0.126      0.900
PercentHispanic                          -0.461      0.246     -1.874      0.061
PercentNonHispanicWhite                  -0.728      0.374     -1.949      0.051
PercentUnder18FEM                        -0.031      0.030     -1.041      0.298
Percent1824FEM                           -0.002      0.028     -0.084      0.933
Percent2544FEM                            0.024      0.035      0.680      0.496
Percent4564FEM                           -0.068      0.029     -2.342      0.019
PercentOVER65FEM                          0.051      0.041      1.231      0.218
```

Figure D2

Geographically Weighted Regression Model for Research Question 1

```
Geographically Weighted Regression (GWR) Results
------------------------------------------------------------------------------
Coordinates type:                                             Projected
Spatial kernel:                                      Adaptive bisquare
Criterion for optimal bandwidth:                                  AICc
Bandwidth used:                                               1229.000

Diagnostic Information
------------------------------------------------------------------------------
Residual sum of squares:                                      2178.540
Effective number of parameters (trace(S)):                     160.967
Degree of freedom (n - trace(S)):                             2574.033
Sigma estimate:                                                  0.920
Log-likelihood:                                              -3569.723
Degree of Dependency (DoD):                                      0.788
AIC:                                                          7463.379
AICc:                                                         7483.904
BIC:                                                          8421.234
R2:                                                              0.203
Adj. R2:                                                         0.154
Adj. alpha (95%):                                                0.009
Adj. critical t value (95%):                                     2.602

Summary Statistics For GWR Parameter Estimates
------------------------------------------------------------------------------
Variable                         Mean        STD        Min     Median        Max
--------------------      ---------- ---------- ---------- ---------- ----------
Intercept                     -0.041      0.128     -0.329     -0.023      0.230
PercentSmokers                -0.072      0.139     -0.455     -0.035      0.102
PercentObese                   0.022      0.076     -0.195      0.027      0.180
FoodEnvironmentIndex          -0.020      0.027     -0.114     -0.022      0.070
PercentFoodInsecure            0.025      0.132     -0.242      0.058      0.235
@20thPercentileIncome         -0.073      0.124     -0.262     -0.081      0.194
IncomeRatio                   -0.024      0.065     -0.244     -0.007      0.086
ChlamydiaRate                  0.023      0.078     -0.204      0.043      0.150
GraduationRate                 0.008      0.036     -0.073      0.009      0.087
PercentSomeCollege            -0.005      0.103     -0.250     -0.012      0.182
PercentSevereHousingProblems      0.008      0.116     -0.177     -0.008      0.410
AgeAdjustedMortality           0.041      0.043     -0.102      0.051      0.158
PercentAdultsUninsured         0.188      0.099     -0.052      0.193      0.367
HealthCareCosts                0.045      0.066     -0.116      0.032      0.160
HouseholdIncome                0.129      0.141     -0.218      0.136      0.416
5.1                            0.039      0.073     -0.131      0.036      0.213
PercentRural                   0.003      0.071     -0.138     -0.002      0.209
HealthBehaviorsRank           -0.042      0.079     -0.195     -0.058      0.205
HealthOutcomesRank             0.010      0.081     -0.277      0.039      0.137
PercentAfricanAmerican        -0.907      0.500     -2.225     -0.959      0.610
PercentAmericanIndianAlaskanNative     -0.613      0.325     -1.592     -0.652      0.176
PercentAsian                  -0.222      0.121     -0.490     -0.222      0.066
PercentNativeHawaiianOtherPacificIslander     -0.117      0.255     -0.753     -0.124      0.420
PercentHispanic               -0.933      0.507     -2.131     -0.953      0.258
PercentNonHispanicWhite       -1.340      0.689     -3.131     -1.405      0.328
PercentUnder18FEM             -0.051      0.042     -0.155     -0.053      0.111
Percent1824FEM                -0.015      0.069     -0.157      0.009      0.077
Percent2544FEM                 0.022      0.066     -0.100      0.026      0.177
Percent4564FEM                -0.040      0.054     -0.172     -0.029      0.057
PercentOVER65FEM               0.016      0.056     -0.101      0.015      0.288
==============================================================================
Acknowledgement:
We acknowledge the support of the National Science Foundation under Award 1758786
from the Geography and Spatial Sciences Program to A. S. Fotheringham which
enabled this software to be written and made freely available.
==============================================================================
```

Figure D3

Multiscale Geographically Weighted Regression Model for Research Question 1

```
Multiscale Geographically Weighted Regression (MGWR) Results
------------------------------------------------------------------------------
Coordinates type:                                                  Projected
Spatial kernel:                                          Adaptive bisquare
Criterion for optimal bandwidth:                                      AICc
Score of change (SOC) type:                                  Smoothing f
Termination criterion for MGWR:                                  1.0e-05
Number of iterations used:                                           200

MGWR bandwidths
------------------------------------------------------------------------------
Variable                  Bandwidth      ENP_j   Adj t-val(95%)           DoD_j
Intercept                  2642.000      1.154            2.022           0.982
PercentSmokers             2506.000      1.438            2.112           0.954
PercentObese               2710.000      1.245            2.053           0.972
FoodEnvironmentIndex       2734.000      1.093            1.999           0.989
PercentFoodInsecure        2734.000      1.048            1.981           0.994
@20thPercentileIncome       2722.000      1.141            2.017           0.983
IncomeRatio                2710.000      1.263            2.059           0.970
ChlamydiaRate              2730.000      1.209            2.041           0.976
GraduationRate             2620.000      1.404            2.102           0.957
PercentSomeCollege         2732.000      1.103            2.002           0.988
PercentSevereHousingProblems       2476.000      2.052            2.252           0.909
AgeAdjustedMortality       2734.000      1.093            1.999           0.989
PercentAdultsUninsured        540.000     11.200            2.846           0.695
HealthCareCosts             612.000     10.983            2.839           0.697
HouseholdIncome             890.000      7.539            2.717           0.745
5.1                        2734.000      1.248            2.054           0.972
PercentRural               2311.000      2.260            2.289           0.897
HealthBehaviorsRank        2734.000      1.046            1.980           0.994
HealthOutcomesRank         2733.000      1.048            1.981           0.994
PercentAfricanAmerican       2722.000      1.031            1.974           0.996
PercentAmericanIndianAlaskanNative        311.000     17.732            2.989           0.637
PercentAsian               2734.000      1.622            2.160           0.939
PercentNativeHawaiianOtherPacificIslander       2734.000      1.253            2.056
0.972
PercentHispanic            2708.000      1.134            2.014           0.984
PercentNonHispanicWhite       2734.000      1.069            1.989           0.992
PercentUnder18FEM          2719.000      1.218            2.044           0.975
Percent1824FEM             2405.000      2.059            2.254           0.909
Percent2544FEM             2734.000      1.162            2.025           0.981
Percent4564FEM             2734.000      1.150            2.020           0.982
PercentOVER65FEM           2734.000      1.143            2.017           0.983

Diagnostic Information
```

Figure D4

Multiscale Geographically Weighted Regression Model for Research Question 1 (Bandwidths)

Diagnostic Information

Residual sum of squares:	2287.109
Effective number of parameters (trace(S)):	81.140
Degree of freedom (n - trace(S)):	2653.860
Sigma estimate:	0.928
Log-likelihood:	-3636.229
Degree of Dependency (DoD):	0.874
AIC:	7436.739
AICc:	7441.890
BIC:	7922.507
R2:	0.164
Adj. R2:	0.138

Summary Statistics For MGWR Parameter Estimates

Variable	Mean	STD	Min	Median	Max
Intercept	0.025	0.011	-0.022	0.030	0.037
PercentSmokers	-0.044	0.019	-0.082	-0.035	-0.024
PercentObese	0.041	0.007	0.029	0.039	0.057
FoodEnvironmentIndex	-0.005	0.002	-0.025	-0.005	-0.003
PercentFoodInsecure	0.066	0.001	0.065	0.066	0.071
@20thPercentileIncome	-0.050	0.002	-0.077	-0.050	-0.044
IncomeRatio	-0.008	0.004	-0.015	-0.009	0.012
ChlamydiaRate	-0.005	0.003	-0.016	-0.004	-0.003
GraduationRate	0.007	0.005	-0.002	0.006	0.023
PercentSomeCollege	-0.032	0.001	-0.041	-0.032	-0.027
PercentSevereHousingProblems	-0.016	0.032	-0.110	-0.007	0.028
AgeAdjustedMortality	0.040	0.002	0.038	0.039	0.061
PercentAdultsUninsured	0.179	0.130	-0.182	0.207	0.415
HealthCareCosts	0.038	0.115	-0.403	0.055	0.241
HouseholdIncome	0.132	0.058	0.013	0.130	0.256
5.1	0.049	0.003	0.047	0.048	0.075
PercentRural	-0.041	0.021	-0.072	-0.046	0.011
HealthBehaviorsRank	-0.073	0.001	-0.074	-0.074	-0.062
HealthOutcomesRank	0.032	0.003	0.029	0.031	0.049
PercentAfricanAmerican	-0.343	0.004	-0.346	-0.344	-0.308
PercentAmericanIndianAlaskanNative	-0.204	0.457	-1.074	-0.283	1.237
PercentAsian	-0.132	0.005	-0.137	-0.134	-0.091
PercentNativeHawaiianOtherPacificIslander	0.020	0.009	-0.001	0.019	0.081
PercentHispanic	-0.359	0.002	-0.365	-0.359	-0.354
PercentNonHispanicWhite	-0.472	0.002	-0.490	-0.472	-0.470
PercentUnder18FEM	-0.054	0.005	-0.061	-0.056	-0.027
Percent1824FEM	0.003	0.015	-0.032	0.011	0.026
Percent2544FEM	0.025	0.003	0.002	0.025	0.027
Percent4564FEM	-0.037	0.002	-0.053	-0.036	-0.035
PercentOVER65FEM	0.021	0.001	0.019	0.021	0.032

Acknowledgement:
We acknowledge the support of the National Science Foundation under Award 1758786
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enabled this software to be written and made freely available.

Appendix E: Ordinary Least Squares, Geographically Weighted Regression, and Multiscale Geographically Weighted Regression for Research Question 2

Figure E1

Ordinary Least Squares Results for Research Question 2

```
========================================================================
MGWR Version: 2.2.1
Released on: 03/20/2020
Source code is available at: https://github.com/pysal/mgwr
Development Team: Ziqi Li, Taylor Oshan, Stewart Fotheringham, Wei Kang,
Levi Wolf, Hanchen Yu, Mehak Sachdeva, and Sarah Bardin
Spatial Analysis Research Center (SPARC)
Arizona State University, Tempe, USA
========================================================================
Model type:                                                    Gaussian
Number of observations:                                            2735
Number of covariates:                                                32
Dependent variable:                                            ADRDPrev
Variable standardization:                                            On
Total runtime:                                                 8:21:15

Global Regression Results
------------------------------------------------------------------------
Residual sum of squares:                                       1907.923
Log-likelihood:                                               -3388.338
AIC:                                                           6840.676
AICc:                                                          6843.507
R2:                                                               0.302
Adj. R2:                                                          0.294

Variable                                   Est.         SE  t(Est/SE)    p-value
---------------------------------- ---------- ---------- ---------- ----------
Intercept                              -0.000      0.016     -0.000      1.000
PercentSmokers                         -0.073      0.032     -2.259      0.024
PercentObese                            0.021      0.026      0.811      0.417
FoodEnvironmentIndex                    0.010      0.025      0.411      0.681
PercentFoodInsecure                     0.109      0.040      2.745      0.006
@20thPercentileIncome                  -0.026      0.060     -0.435      0.664
IncomeRatio                            -0.033      0.029     -1.129      0.259
ChlamydiaRate                           0.030      0.029      1.044      0.297
GraduationRate                         -0.013      0.021     -0.614      0.539
PercentSomeCollege                      0.018      0.030      0.605      0.545
PercentSevereHousingProblems           -0.046      0.025     -1.843      0.065
AgeAdjustedMortality                    0.012      0.029      0.428      0.668
PercentAdultsUninsured                  0.154      0.027      5.651      0.000
HealthCareCosts                         0.076      0.021      3.671      0.000
HouseholdIncome                         0.117      0.055      2.120      0.034
5.1                                    -0.019      0.025     -0.759      0.448
PercentRural                           -0.003      0.026     -0.113      0.910
HealthBehaviorsRank                    -0.020      0.032     -0.640      0.522
HealthOutcomesRank                      0.053      0.032      1.665      0.096
PercentAfricanAmerican                 -0.395      0.228     -1.735      0.083
PercentAmericanIndianAlaskanNative     -0.259      0.132     -1.960      0.050
PercentAsian                           -0.097      0.054     -1.790      0.073
PercentNativeHawaiianOtherPacificIslander     -0.028      0.030     -0.920      0.358
PercentHispanic                        -0.319      0.215     -1.483      0.138
PercentNonHispanicWhite                -0.516      0.327     -1.580      0.114
PercentUnder18FEM                      -0.027      0.026     -1.030      0.303
Percent1824FEM                         -0.010      0.025     -0.398      0.690
Percent2544FEM                         -0.005      0.031     -0.166      0.868
Percent4564FEM                         -0.085      0.025     -3.376      0.001
PercentOVER65FEM                        0.053      0.036      1.478      0.139
T2DMPrevU                               0.111      0.037      2.994      0.003
T2DMPrevO                               0.386      0.038     10.213      0.000
```

Figure E2

Geographically Weighted Regression Results for Research Question 2

```
Geographically Weighted Regression (GWR) Results
------------------------------------------------------------------------------
Coordinates type:                                            Projected
Spatial kernel:                                   Adaptive bisquare
Criterion for optimal bandwidth:                               AICc
Bandwidth used:                                            1177.000

Diagnostic Information
------------------------------------------------------------------------------
Residual sum of squares:                                   1634.845
Effective number of parameters (trace(S)):                  180.466
Degree of freedom (n - trace(S)):                          2554.534
Sigma estimate:                                               0.800
Log-likelihood:                                           -3177.104
Degree of Dependency (DoD):                                   0.781
AIC:                                                       6717.140
AICc:                                                      6743.084
BIC:                                                       7790.311
R2:                                                           0.402
Adj. R2:                                                      0.360
Adj. alpha (95%):                                             0.009
Adj. critical t value (95%):                                  2.619

Summary Statistics For GWR Parameter Estimates
------------------------------------------------------------------------------
Variable                         Mean        STD        Min     Median        Max
--------------------      ---------- ---------- ---------- ---------- ----------
Intercept                     -0.074      0.129     -0.308     -0.070      0.160
PercentSmokers                -0.060      0.131     -0.421     -0.023      0.111
PercentObese                   0.010      0.053     -0.184      0.011      0.156
FoodEnvironmentIndex           0.003      0.022     -0.055      0.003      0.053
PercentFoodInsecure            0.055      0.101     -0.150      0.088      0.218
@20thPercentileIncome         -0.036      0.110     -0.228     -0.033      0.199
IncomeRatio                   -0.042      0.059     -0.179     -0.029      0.050
ChlamydiaRate                  0.020      0.080     -0.199      0.045      0.142
GraduationRate                -0.010      0.021     -0.059     -0.011      0.040
PercentSomeCollege            -0.004      0.078     -0.215      0.025      0.107
PercentSevereHousingProblems      0.005      0.103     -0.172      0.009      0.314
AgeAdjustedMortality           0.033      0.041     -0.073      0.032      0.178
PercentAdultsUninsured         0.122      0.075     -0.066      0.129      0.250
HealthCareCosts                0.034      0.060     -0.102      0.028      0.143
HouseholdIncome                0.096      0.110     -0.161      0.097      0.294
5.1                            0.027      0.095     -0.127      0.010      0.265
PercentRural                  -0.019      0.074     -0.154     -0.027      0.163
HealthBehaviorsRank           -0.008      0.088     -0.158     -0.025      0.235
HealthOutcomesRank             0.000      0.075     -0.229      0.000      0.129
PercentAfricanAmerican        -0.808      0.635     -2.208     -0.994      0.783
PercentAmericanIndianAlaskanNative     -0.583      0.365     -1.376     -0.712      0.248
PercentAsian                  -0.184      0.116     -0.461     -0.194      0.100
PercentNativeHawaiianOtherPacificIslander     -0.049      0.150     -0.367     -0.063      0.295
PercentHispanic               -0.836      0.558     -1.953     -0.903      0.489
PercentNonHispanicWhite       -1.220      0.783     -3.104     -1.355      0.717
PercentUnder18FEM             -0.040      0.054     -0.164     -0.021      0.087
Percent1824FEM                -0.008      0.045     -0.102      0.007      0.056
Percent2544FEM                 0.003      0.045     -0.086      0.006      0.080
Percent4564FEM                -0.048      0.043     -0.145     -0.056      0.072
PercentOVER65FEM               0.052      0.043     -0.061      0.052      0.213
T2DMPrevU                      0.128      0.094     -0.004      0.132      0.344
T2DMPrevO                      0.352      0.082      0.181      0.347      0.495
==============================================================================
Acknowledgement:
We acknowledge the support of the National Science Foundation under Award 1758786
from the Geography and Spatial Sciences Program to A. S. Fotheringham which
enabled this software to be written and made freely available.
==============================================================================
```

Figure E3

Multiscale Geographically Weighted Regression Results for Research Question 2

```
Multiscale Geographically Weighted Regression (MGWR) Results
------------------------------------------------------------------------------
Coordinates type:                                                    Projected
Spatial kernel:                                                Adaptive bisquare
Criterion for optimal bandwidth:                                           AICc
Score of change (SOC) type:                                       Smoothing f
Termination criterion for MGWR:                                      1.0e-05
Number of iterations used:                                               200

MGWR bandwidths
------------------------------------------------------------------------------
Variable                  Bandwidth      ENP_j   Adj t-val(95%)           DoD_j
Intercept                  2722.000      1.042            1.978           0.995
PercentSmokers              117.000     56.281            3.327           0.491
PercentObese               2717.000      1.133            2.014           0.984
FoodEnvironmentIndex       2734.000      1.086            1.996           0.990
PercentFoodInsecure        2734.000      1.041            1.978           0.995
@20thPercentileIncome       2734.000      1.124            2.010           0.985
IncomeRatio                2734.000      1.119            2.009           0.986
ChlamydiaRate              2734.000      1.174            2.029           0.980
GraduationRate             2502.000      1.495            2.128           0.949
PercentSomeCollege         2734.000      1.089            1.997           0.989
PercentSevereHousingProblems       2291.000      2.226            2.284           0.899
AgeAdjustedMortality       2734.000      1.073            1.991           0.991
PercentAdultsUninsured       2734.000      1.069            1.989           0.992
HealthCareCosts            1905.000      2.653            2.350           0.877
HouseholdIncome            2734.000      1.116            2.007           0.986
5.1                        2734.000      1.202            2.038           0.977
PercentRural               1782.000      3.253            2.425           0.851
HealthBehaviorsRank        2195.000      1.662            2.170           0.936
HealthOutcomesRank         2292.000      1.684            2.175           0.934
PercentAfricanAmerican       1312.000      2.351            2.305           0.892
PercentAmericanIndianAlaskanNative        507.000      9.461            2.791           0.716
PercentAsian               2732.000      1.550            2.142           0.945
PercentNativeHawaiianOtherPacificIslander       2734.000      1.225            2.046
0.974
PercentHispanic             684.000      8.046            2.738           0.737
PercentNonHispanicWhite       2732.000      1.053            1.983           0.993
PercentUnder18FEM          2734.000      1.130            2.013           0.985
Percent1824FEM             2728.000      1.142            2.017           0.983
Percent2544FEM             2621.000      1.558            2.144           0.944
Percent4564FEM             2734.000      1.131            2.013           0.984
PercentOVER65FEM           2734.000      1.130            2.013           0.985
T2DMPrevU                    43.000    158.177            3.606           0.360
T2DMPrevO                   578.000      6.191            2.651           0.770

Diagnostic Information
```

Figure E4

Multiscale Geographically Weighted Regression Results for Research Question 2 (Bandwidths)

```
Diagnostic Information
---------------------------------------------------------------------------
Residual sum of squares:                                          1273.834
Effective number of parameters (trace(S)):                         276.665
Degree of freedom (n - trace(S)):                                 2458.335
Sigma estimate:                                                      0.720
Log-likelihood:                                                  -2835.890
Degree of Dependency (DoD):                                          0.727
AIC:                                                             6227.111
AICc:                                                            6290.112
BIC:                                                             7869.191
R2:                                                                  0.534
Adj. R2:                                                             0.482

Summary Statistics For MGWR Parameter Estimates
---------------------------------------------------------------------------
Variable                       Mean        STD        Min     Median        Max
--------------------      ---------- ---------- ---------- ---------- ----------
Intercept                     -0.047      0.003     -0.064     -0.046     -0.045
PercentSmokers                -0.056      0.203     -0.741     -0.035      0.524
PercentObese                   0.064      0.003      0.059      0.063      0.074
FoodEnvironmentIndex           0.003      0.000      0.003      0.003      0.007
PercentFoodInsecure            0.065      0.001      0.059      0.066      0.066
@20thPercentileIncome         -0.059      0.002     -0.078     -0.058     -0.058
IncomeRatio                   -0.015      0.002     -0.017     -0.015     -0.002
ChlamydiaRate                  0.016      0.001      0.011      0.017      0.018
GraduationRate                -0.043      0.007     -0.059     -0.042     -0.029
PercentSomeCollege            -0.009      0.000     -0.011     -0.009     -0.007
PercentSevereHousingProblems      0.008      0.037     -0.103      0.011      0.062
AgeAdjustedMortality           0.033      0.001      0.033      0.033      0.041
PercentAdultsUninsured         0.112      0.000      0.110      0.112      0.115
HealthCareCosts                0.040      0.029     -0.029      0.044      0.098
HouseholdIncome                0.121      0.001      0.113      0.121      0.122
5.1                            0.010      0.003      0.008      0.009      0.035
PercentRural                  -0.052      0.024     -0.092     -0.054     -0.009
HealthBehaviorsRank           -0.044      0.029     -0.090     -0.044      0.008
HealthOutcomesRank             0.010      0.028     -0.036      0.008      0.053
PercentAfricanAmerican        -0.483      0.051     -0.536     -0.493     -0.257
PercentAmericanIndianAlaskanNative     -0.339      0.129     -0.523     -0.375      0.116
PercentAsian                  -0.096      0.005     -0.100     -0.097     -0.057
PercentNativeHawaiianOtherPacificIslander     -0.017      0.003     -0.025     -0.017     -0.005
PercentHispanic               -0.444      0.076     -0.604     -0.435     -0.329
PercentNonHispanicWhite       -0.617      0.001     -0.623     -0.617     -0.614
PercentUnder18FEM             -0.047      0.001     -0.048     -0.047     -0.044
Percent1824FEM                -0.021      0.004     -0.024     -0.022      0.002
Percent2544FEM                -0.015      0.007     -0.037     -0.012     -0.007
Percent4564FEM                -0.063      0.002     -0.072     -0.063     -0.062
PercentOVER65FEM               0.049      0.001      0.046      0.049      0.052
T2DMPrevU                      0.197      0.340     -0.693      0.159      1.136
T2DMPrevO                      0.327      0.115      0.110      0.359      0.540
===========================================================================
Acknowledgement:
We acknowledge the support of the National Science Foundation under Award 1758786
from the Geography and Spatial Sciences Program to A. S. Fotheringham which
enabled this software to be written and made freely available.
===========================================================================
```

Appendix F: Ordinary Least Squares, Geographically Weighted Regression, and Multiscale Geographically Weighted Regression for Research Question 3

Figure F1

Ordinary Least Square Results for RQ3

```
==========================================================================
MGWR Version: 2.2.1
Released on: 03/20/2020
Source code is available at: https://github.com/pysal/mgwr
Development Team: Ziqi Li, Taylor Oshan, Stewart Fotheringham, Wei Kang,
Levi Wolf, Hanchen Yu, Mehak Sachdeva, and Sarah Bardin
Spatial Analysis Research Center (SPARC)
Arizona State University, Tempe, USA
==========================================================================
Model type:                                                      Gaussian
Number of observations:                                              3142
Number of covariates:                                                 32
Dependent variable:                                            ADRDPrev
Variable standardization:                                            On
Total runtime:                                                 0:01:42

Global Regression Results
--------------------------------------------------------------------------
Residual sum of squares:                                       1878.237
Log-likelihood:                                               -3649.984
AIC:                                                           7363.969
AICc:                                                          7366.691
R2:                                                               0.402
Adj. R2:                                                          0.396

Variable                                   Est.         SE  t(Est/SE)    p-value
---------------------------------- ---------- ---------- ---------- ----------
Intercept                               0.000      0.014      0.000      1.000
PercentSmokers                         -0.075      0.028     -2.700      0.007
PercentObese                            0.014      0.022      0.650      0.516
FoodEnvironmentIndex                    0.024      0.021      1.133      0.257
PercentFoodInsecure                     0.123      0.033      3.719      0.000
@20thPercentileIncome                  -0.014      0.055     -0.264      0.791
IncomeRatio                            -0.021      0.025     -0.836      0.403
ChlamydiaRate                           0.022      0.025      0.874      0.382
GraduationRate                         -0.012      0.018     -0.658      0.511
PercentSomeCollege                      0.029      0.026      1.118      0.264
PercentSevereHousingProblems           -0.049      0.021     -2.307      0.021
AgeAdjustedMortality                   -0.029      0.025     -1.145      0.252
PercentAdultsUninsured                  0.142      0.023      6.115      0.000
HealthCareCosts                         0.083      0.018      4.714      0.000
HouseholdIncome                         0.074      0.051      1.458      0.145
5.1                                    -0.028      0.021     -1.354      0.176
PercentRural                           -0.018      0.022     -0.813      0.416
HealthBehaviorsRank                    -0.020      0.027     -0.724      0.469
HealthOutcomesRank                      0.050      0.028      1.775      0.076
PercentAfricanAmerican                 -0.257      0.197     -1.301      0.193
PercentAmericanIndianAlaskanNative     -0.163      0.111     -1.465      0.143
PercentAsian                           -0.077      0.047     -1.630      0.103
PercentNativeHawaiianOtherPacificIslander     -0.012      0.025     -0.485      0.627
PercentHispanic                        -0.136      0.183     -0.746      0.455
PercentNonHispanicWhite                -0.276      0.280     -0.986      0.324
PercentUnder18FEM                      -0.037      0.023     -1.625      0.104
Percent1824FEM                         -0.027      0.021     -1.281      0.200
Percent2544FEM                         -0.014      0.026     -0.524      0.601
Percent4564FEM                         -0.062      0.022     -2.837      0.005
PercentOVER65FEM                        0.011      0.031      0.342      0.732
HypertensionPrevU                       0.075      0.038      1.958      0.050
HypertensionPrevO                       0.519      0.038     13.714      0.000
```

Figure F2

Geographically Weighted Regression Results for Research Question 3

```
Geographically Weighted Regression (GWR) Results
------------------------------------------------------------------------------
Coordinates type:                                                    Projected
Spatial kernel:                                             Adaptive bisquare
Criterion for optimal bandwidth:                                         AICc
Bandwidth used:                                                      1224.000

Diagnostic Information
------------------------------------------------------------------------------
Residual sum of squares:                                             1619.541
Effective number of parameters (trace(S)):                            202.741
Degree of freedom (n - trace(S)):                                    2939.259
Sigma estimate:                                                         0.742
Log-likelihood:                                                     -3417.177
Degree of Dependency (DoD):                                             0.771
AIC:                                                                 7241.837
AICc:                                                                7270.241
BIC:                                                                 8475.006
R2:                                                                     0.485
Adj. R2:                                                                0.449
Adj. alpha (95%):                                                       0.008
Adj. critical t value (95%):                                            2.658

Summary Statistics For GWR Parameter Estimates
------------------------------------------------------------------------------
Variable                       Mean        STD        Min     Median        Max
--------------------      ---------- ---------- ---------- ---------- ----------
Intercept                     -0.070      0.105     -0.240     -0.090      0.165
PercentSmokers                -0.043      0.104     -0.311     -0.012      0.100
PercentObese                   0.006      0.044     -0.133      0.004      0.112
FoodEnvironmentIndex           0.013      0.026     -0.079      0.015      0.072
PercentFoodInsecure            0.032      0.079     -0.127      0.040      0.169
@20thPercentileIncome         -0.046      0.099     -0.269     -0.052      0.194
IncomeRatio                   -0.026      0.051     -0.163     -0.021      0.065
ChlamydiaRate                  0.019      0.065     -0.134      0.037      0.132
GraduationRate                -0.006      0.030     -0.055     -0.013      0.066
PercentSomeCollege             0.015      0.057     -0.142      0.030      0.135
PercentSevereHousingProblems     -0.019      0.058     -0.168     -0.009      0.135
AgeAdjustedMortality          -0.003      0.042     -0.100      0.001      0.109
PercentAdultsUninsured         0.109      0.050     -0.043      0.108      0.272
HealthCareCosts                0.046      0.051     -0.061      0.040      0.142
HouseholdIncome                0.059      0.093     -0.126      0.054      0.281
5.1                            0.016      0.078     -0.165      0.015      0.174
PercentRural                  -0.026      0.063     -0.150     -0.028      0.135
HealthBehaviorsRank           -0.018      0.104     -0.254     -0.033      0.301
HealthOutcomesRank             0.008      0.085     -0.213      0.012      0.229
PercentAfricanAmerican        -0.551      0.755     -1.772     -0.728      1.090
PercentAmericanIndianAlaskanNative     -0.343      0.418     -1.036     -0.510      0.556
PercentAsian                  -0.141      0.164     -0.459     -0.146      0.205
PercentNativeHawaiianOtherPacificIslander     -0.066      0.129     -0.754     -0.051      0.236
PercentHispanic               -0.501      0.770     -1.779     -0.669      1.188
PercentNonHispanicWhite       -0.775      1.098     -2.512     -1.045      1.720
PercentUnder18FEM             -0.048      0.050     -0.183     -0.046      0.070
Percent1824FEM                -0.020      0.039     -0.096     -0.021      0.060
Percent2544FEM                -0.004      0.040     -0.121     -0.005      0.083
Percent4564FEM                -0.033      0.053     -0.186     -0.042      0.089
PercentOVER65FEM               0.011      0.059     -0.101      0.005      0.177
HypertensionPrevU              0.064      0.085     -0.182      0.067      0.239
HypertensionPrev0              0.504      0.096      0.248      0.489      0.736
==============================================================================
Acknowledgement:
We acknowledge the support of the National Science Foundation under Award 1758786
from the Geography and Spatial Sciences Program to A. S. Fotheringham which
enabled this software to be written and made freely available.
==============================================================================
```

Figure F3

Multiscale Geographically Weighted Regression Results for Research Question 3

```
Multiscale Geographically Weighted Regression (MGWR) Results
------------------------------------------------------------------------------
Coordinates type:                                                   Projected
Spatial kernel:                                           Adaptive bisquare
Criterion for optimal bandwidth:                                       AICc
Score of change (SOC) type:                                   Smoothing f
Termination criterion for MGWR:                                  1.0e-05
Number of iterations used:                                           200

MGWR bandwidths
------------------------------------------------------------------------------
Variable                  Bandwidth      ENP_j   Adj t-val(95%)           DoD_j
Intercept                  2733.000      1.036            1.976           0.996
PercentSmokers              132.000     48.847            3.287           0.509
PercentObese               2732.000      1.099            2.001           0.988
FoodEnvironmentIndex       2734.000      1.088            1.997           0.989
PercentFoodInsecure        2734.000      1.045            1.980           0.994
@20thPercentileIncome       2734.000      1.121            2.009           0.986
IncomeRatio                2713.000      1.228            2.047           0.974
ChlamydiaRate              2734.000      1.171            2.028           0.980
GraduationRate             2336.000      1.813            2.204           0.925
PercentSomeCollege         2734.000      1.094            1.999           0.989
PercentSevereHousingProblems       2484.000      1.889            2.220           0.920
AgeAdjustedMortality       2734.000      1.075            1.992           0.991
PercentAdultsUninsured       2734.000      1.073            1.991           0.991
HealthCareCosts            1250.000      4.604            2.549           0.807
HouseholdIncome            2734.000      1.115            2.007           0.986
5.1                        2734.000      1.201            2.038           0.977
PercentRural               2331.000      2.149            2.270           0.903
HealthBehaviorsRank        1859.000      2.184            2.277           0.901
HealthOutcomesRank         2292.000      1.679            2.174           0.935
PercentAfricanAmerican       2734.000      1.018            1.968           0.998
PercentAmericanIndianAlaskanNative        630.000      8.044            2.738           0.737
PercentAsian               2732.000      1.519            2.134           0.947
PercentNativeHawaiianOtherPacificIslander       2734.000      1.236            2.050
0.973
PercentHispanic            2723.000      1.069            1.989           0.992
PercentNonHispanicWhite       2734.000      1.062            1.987           0.992
PercentUnder18FEM          2734.000      1.132            2.014           0.984
Percent1824FEM             2728.000      1.143            2.017           0.983
Percent2544FEM             2529.000      1.787            2.199           0.927
Percent4564FEM             2734.000      1.139            2.016           0.984
PercentOVER65FEM           2734.000      1.133            2.014           0.984
HypertensionPrevU            43.000    161.588            3.612           0.357
HypertensionPrevO          2734.000      1.030            1.973           0.996
```

Figure F4

Multiscale Geographically Weighted Regression Results for Research Question 3 (Bandwidths)

Diagnostic Information

Residual sum of squares:	1193.258
Effective number of parameters (trace(S)):	259.410
Degree of freedom (n - trace(S)):	2475.590
Sigma estimate:	0.694
Log-likelihood:	-2746.533
Degree of Dependency (DoD):	0.736
AIC:	6013.886
AICc:	6068.926
BIC:	7553.924
R2:	0.564
Adj. R2:	0.518

Summary Statistics For MGWR Parameter Estimates

Variable	Mean	STD	Min	Median	Max
Intercept	-0.074	0.002	-0.088	-0.073	-0.072
PercentSmokers	-0.074	0.201	-0.714	-0.054	0.331
PercentObese	0.035	0.002	0.033	0.035	0.042
FoodEnvironmentIndex	0.003	0.000	0.001	0.003	0.003
PercentFoodInsecure	0.037	0.001	0.033	0.038	0.038
@20thPercentileIncome	-0.029	0.002	-0.049	-0.029	-0.029
IncomeRatio	0.008	0.004	0.003	0.007	0.024
ChlamydiaRate	-0.003	0.001	-0.015	-0.003	-0.003
GraduationRate	-0.020	0.017	-0.047	-0.019	0.008
PercentSomeCollege	-0.010	0.000	-0.011	-0.010	-0.008
PercentSevereHousingProblems	-0.030	0.020	-0.114	-0.026	-0.004
AgeAdjustedMortality	0.006	0.001	0.005	0.005	0.017
PercentAdultsUninsured	0.056	0.002	0.055	0.056	0.071
HealthCareCosts	0.032	0.044	-0.101	0.041	0.130
HouseholdIncome	0.064	0.001	0.055	0.064	0.065
5.1	-0.028	0.004	-0.030	-0.029	0.003
PercentRural	-0.043	0.012	-0.065	-0.044	-0.020
HealthBehaviorsRank	-0.029	0.050	-0.106	-0.025	0.059
HealthOutcomesRank	0.034	0.027	-0.011	0.033	0.081
PercentAfricanAmerican	-0.587	0.001	-0.588	-0.587	-0.572
PercentAmericanIndianAlaskanNative	-0.454	0.082	-0.637	-0.455	-0.184
PercentAsian	-0.125	0.005	-0.128	-0.126	-0.087
PercentNativeHawaiianOtherPacificIslander	-0.052	0.014	-0.089	-0.051	-0.021
PercentHispanic	-0.477	0.001	-0.480	-0.477	-0.476
PercentNonHispanicWhite	-0.813	0.001	-0.822	-0.813	-0.812
PercentUnder18FEM	-0.042	0.001	-0.046	-0.042	-0.039
Percent1824FEM	-0.016	0.003	-0.019	-0.017	0.002
Percent2544FEM	-0.006	0.010	-0.029	-0.002	0.006
Percent4564FEM	-0.067	0.001	-0.073	-0.066	-0.065
PercentOVER65FEM	0.045	0.001	0.043	0.045	0.051
HypertensionPrevU	0.010	0.312	-0.934	0.043	0.914
HypertensionPrevO	0.600	0.001	0.597	0.600	0.603

Acknowledgement:
We acknowledge the support of the National Science Foundation under Award 1758786
from the Geography and Spatial Sciences Program to A. S. Fotheringham which
enabled this software to be written and made freely available.

Appendix G: Ordinary Least Squares, Geographically Weighted Regression, and Multiscale Geographically Weighted Regression for Research Question 4

Figure G1

Ordinary Least Square Results for Research Question 4

```
================================================================================
MGWR Version: 2.2.1
Released on: 03/20/2020
Source code is available at: https://github.com/pysal/mgwr
Development Team: Ziqi Li, Taylor Oshan, Stewart Fotheringham, Wei Kang,
Levi Wolf, Hanchen Yu, Mehak Sachdeva, and Sarah Bardin
Spatial Analysis Research Center (SPARC)
Arizona State University, Tempe, USA
================================================================================
Model type:                                                            Gaussian
Number of observations:                                                    2735
Number of covariates:                                                        38
Dependent variable:                                                    ADRDPrev
Variable standardization:                                                    On
Total runtime:                                                          0:01:23

Global Regression Results
--------------------------------------------------------------------------------
Residual sum of squares:                                              1570.253
Log-likelihood:                                                      -3121.978
AIC:                                                                  6319.956
AICc:                                                                 6323.114
R2:                                                                      0.426
Adj. R2:                                                                 0.418

Variable                                   Est.         SE  t(Est/SE)    p-value
---------------------------------- ------------ ---------- ---------- ----------
Intercept                             0.000      0.015      0.000      1.000
PercentSmokers                       -0.098      0.029     -3.318      0.001
PercentObese                          0.011      0.024      0.462      0.644
FoodEnvironmentIndex                  0.014      0.023      0.599      0.549
PercentFoodInsecure                   0.106      0.036      2.947      0.003
@20thPercentileIncome                -0.016      0.054     -0.302      0.763
IncomeRatio                          -0.030      0.027     -1.113      0.266
ChlamydiaRate                        -0.005      0.027     -0.174      0.862
GraduationRate                       -0.018      0.019     -0.941      0.346
PercentSomeCollege                    0.022      0.027      0.808      0.419
PercentSevereHousingProblems         -0.050      0.023     -2.231      0.026
AgeAdjustedMortality                 -0.024      0.026     -0.929      0.353
PercentAdultsUninsured                0.109      0.025      4.363      0.000
HealthCareCosts                       0.075      0.019      3.987      0.000
HouseholdIncome                       0.067      0.050      1.327      0.184
5.1                                  -0.049      0.022     -2.204      0.028
PercentRural                         -0.034      0.024     -1.447      0.148
HealthBehaviorsRank                  -0.006      0.029     -0.213      0.832
HealthOutcomesRank                    0.067      0.029      2.285      0.022
PercentAfricanAmerican               -0.305      0.207     -1.470      0.142
PercentAmericanIndianAlaskanNative   -0.164      0.120     -1.364      0.172
PercentAsian                         -0.075      0.049     -1.528      0.127
PercentNativeHawaiianOtherPacificIslander     -0.017      0.027     -0.621      0.535
PercentHispanic                      -0.210      0.196     -1.071      0.284
PercentNonHispanicWhite              -0.373      0.298     -1.254      0.210
PercentUnder18FEM                    -0.032      0.024     -1.345      0.179
Percent1824FEM                       -0.020      0.022     -0.910      0.363
Percent2544FEM                       -0.011      0.028     -0.390      0.696
Percent4564FEM                       -0.079      0.023     -3.420      0.001
PercentOVER65FEM                      0.022      0.033      0.680      0.496
T2DMPrevU                             0.114      0.038      3.028      0.002
T2DMPrevO                            -0.154      0.043     -3.583      0.000
HypertensionPrevU                    -0.019      0.045     -0.412      0.680
HypertensionPrevO                     0.509      0.048     10.624      0.000
OPPrevU                              -0.142      0.028     -4.997      0.000
OPPrevO                               0.176      0.028      6.244      0.000
SZOthePsychdisdPrevU                 -0.065      0.022     -2.914      0.004
SZOthePsychdisdPrevO                  0.282      0.024     11.666      0.000
```

Figure G2

Geographically Weighted Regression Results for Research Question 4

```
Geographically Weighted Regression (GWR) Results
------------------------------------------------------------------------------
Coordinates type:                                                    Projected
Spatial kernel:                                          Adaptive bisquare
Criterion for optimal bandwidth:                                         AICc
Bandwidth used:                                                      1092.000

Diagnostic Information
------------------------------------------------------------------------------
Residual sum of squares:                                             1286.900
Effective number of parameters (trace(S)):                            231.564
Degree of freedom (n - trace(S)):                                    2503.436
Sigma estimate:                                                         0.717
Log-likelihood:                                                     -2849.845
Degree of Dependency (DoD):                                             0.772
AIC:                                                                 6164.819
AICc:                                                                6208.249
BIC:                                                                 7540.179
R2:                                                                     0.529
Adj. R2:                                                                0.486
Adj. alpha (95%):                                                       0.008
Adj. critical t value (95%):                                            2.645

Summary Statistics For GWR Parameter Estimates
------------------------------------------------------------------------------
Variable                       Mean        STD        Min     Median        Max
-------------------- ---------- ---------- ---------- ---------- ----------
Intercept                  -0.071      0.150     -0.339     -0.051      0.515
PercentSmokers             -0.062      0.109     -0.396     -0.029      0.105
PercentObese               -0.007      0.051     -0.152     -0.014      0.154
FoodEnvironmentIndex        0.002      0.034     -0.083      0.002      0.085
PercentFoodInsecure         0.062      0.112     -0.203      0.100      0.228
@20thPercentileIncome      -0.048      0.110     -0.284     -0.057      0.163
IncomeRatio                -0.040      0.059     -0.176     -0.034      0.053
ChlamydiaRate              -0.020      0.063     -0.192     -0.001      0.076
GraduationRate             -0.006      0.024     -0.047     -0.008      0.056
PercentSomeCollege         -0.001      0.070     -0.184      0.015      0.117
PercentSevereHousingProblems      0.007      0.089     -0.169     -0.001      0.281
AgeAdjustedMortality       -0.005      0.036     -0.074     -0.008      0.145
PercentAdultsUninsured      0.050      0.062     -0.121      0.065      0.234
HealthCareCosts             0.053      0.055     -0.083      0.056      0.154
HouseholdIncome             0.066      0.109     -0.152      0.059      0.258
5.1                         0.018      0.092     -0.121     -0.004      0.200
PercentRural               -0.038      0.066     -0.166     -0.043      0.160
HealthBehaviorsRank         0.009      0.075     -0.125     -0.000      0.208
HealthOutcomesRank         -0.001      0.079     -0.228      0.006      0.136
PercentAfricanAmerican     -0.772      0.721     -2.040     -0.956      0.999
PercentAmericanIndianAlaskanNative     -0.489      0.396     -1.157     -0.590      0.466
PercentAsian               -0.185      0.130     -0.392     -0.223      0.112
PercentNativeHawaiianOtherPacificIslander     -0.077      0.182     -0.649     -0.089      0.292
PercentHispanic            -0.724      0.622     -1.675     -0.788      0.691
PercentNonHispanicWhite    -1.156      0.915     -2.739     -1.375      0.973
PercentUnder18FEM          -0.018      0.048     -0.153     -0.011      0.088
Percent1824FEM             -0.002      0.037     -0.083      0.004      0.070
Percent2544FEM             -0.012      0.051     -0.111     -0.010      0.077
Percent4564FEM             -0.033      0.046     -0.160     -0.039      0.064
PercentOVER65FEM            0.050      0.041     -0.075      0.053      0.186
T2DMPrevU                   0.090      0.094     -0.085      0.083      0.271
T2DMPrevO                  -0.182      0.148     -0.488     -0.191      0.100
HypertensionPrevU          -0.021      0.089     -0.246     -0.020      0.247
HypertensionPrevO           0.571      0.162      0.102      0.574      0.893
OPPrevU                    -0.126      0.089     -0.280     -0.105      0.037
OPPrevO                     0.151      0.090      0.020      0.110      0.364
SZOthePsychdisdPrevU       -0.032      0.079     -0.205     -0.045      0.103
SZOthePsychdisdPrevO        0.249      0.045      0.133      0.246      0.439
==============================================================================
Acknowledgement:
We acknowledge the support of the National Science Foundation under Award 1758786
from the Geography and Spatial Sciences Program to A. S. Fotheringham which
enabled this software to be written and made freely available.
==============================================================================
```

Figure G3

Multiscale Geographically Weighted Regression Results for Research Question 4.

```
Multiscale Geographically Weighted Regression (MGWR) Results
------------------------------------------------------------------------------
Coordinates type:                                                    Projected
Spatial kernel:                                              Adaptive bisquare
Criterion for optimal bandwidth:                                         AICc
Score of change (SOC) type:                                     Smoothing f
Termination criterion for MGWR:                                     1.0e-05
Number of iterations used:                                              200

MGWR bandwidths
------------------------------------------------------------------------------
Variable                  Bandwidth      ENP_j   Adj t-val(95%)           DoD_j
Intercept                  2732.000      1.038            1.977           0.995
PercentSmokers             1591.000      2.759            2.364           0.872
PercentObese               2734.000      1.110            2.005           0.987
FoodEnvironmentIndex       2734.000      1.090            1.998           0.989
PercentFoodInsecure        2734.000      1.045            1.980           0.994
@20thPercentileIncome       2669.000      1.377            2.094           0.960
IncomeRatio                2717.000      1.164            2.025           0.981
ChlamydiaRate              2734.000      1.178            2.030           0.979
GraduationRate             2257.000      1.929            2.229           0.917
PercentSomeCollege         2734.000      1.089            1.997           0.989
PercentSevereHousingProblems       2609.000      1.606            2.156           0.940
AgeAdjustedMortality       2729.000      1.092            1.998           0.989
PercentAdultsUninsured       2730.000      1.077            1.992           0.991
HealthCareCosts            2327.000      1.924            2.228           0.917
HouseholdIncome            2596.000      1.519            2.134           0.947
5.1                        2732.000      1.196            2.036           0.977
PercentRural               2705.000      1.335            2.082           0.963
HealthBehaviorsRank        2734.000      1.036            1.976           0.996
HealthOutcomesRank         2335.000      1.669            2.172           0.935
PercentAfricanAmerican       2734.000      1.014            1.967           0.998
PercentAmericanIndianAlaskanNative        686.000      7.073           2.696
0.753
PercentAsian               2734.000      1.435            2.111           0.954
PercentNativeHawaiianOtherPacificIslander       2734.000      1.228           2.047
0.974
PercentHispanic            2713.000      1.036            1.976           0.996
PercentNonHispanicWhite        137.000     48.594            3.286           0.509
PercentUnder18FEM          2734.000      1.142            2.017           0.983
Percent1824FEM             2734.000      1.121            2.009           0.986
Percent2544FEM             2621.000      1.545            2.141           0.945
Percent4564FEM             2732.000      1.141            2.017           0.983
PercentOVER65FEM           2734.000      1.118            2.008           0.986
T2DMPrevU                    43.000    153.754            3.599           0.364
T2DMPrevO                  2721.000      1.038            1.977           0.995
HypertensionPrevU          2734.000      1.030            1.973           0.996
HypertensionPrevO           159.000     29.108            3.138           0.574
OPPrevU                    1488.000      3.212            2.420           0.853
OPPrevO                     923.000      6.403            2.662           0.765
SZOthePsychdisdPrevU        206.000     32.118            3.167           0.562
SZOthePsychdisdPrevO        605.000      7.953            2.735           0.738
```

Figure G4

Multiscale Geographically Weighted Regression Results for Research Question 4. (Bandwidths)

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Diagnostic Information
---------------------------------------------------------------------------
Residual sum of squares:                                          1024.004
Effective number of parameters (trace(S)):                         327.295
Degree of freedom (n - trace(S)):                                 2407.705
Sigma estimate:                                                      0.652
Log-likelihood:                                                  -2537.350
Degree of Dependency (DoD):                                          0.728
AIC:                                                             5731.289
AICc:                                                            5821.164
BIC:                                                             7672.788
R2:                                                                  0.626
Adj. R2:                                                             0.575

Summary Statistics For MGWR Parameter Estimates
---------------------------------------------------------------------------
Variable                       Mean        STD        Min     Median        Max
--------------------      ---------- ---------- ---------- ---------- ----------
Intercept                    -0.020      0.001     -0.027     -0.020     -0.017
PercentSmokers               -0.084      0.057     -0.198     -0.059     -0.027
PercentObese                  0.022      0.001      0.021      0.022      0.030
FoodEnvironmentIndex          0.007      0.001     -0.005      0.007      0.008
PercentFoodInsecure           0.045      0.001      0.044      0.044      0.054
@20thPercentileIncome        -0.028      0.004     -0.061     -0.030     -0.021
IncomeRatio                  -0.005      0.001     -0.009     -0.005     -0.002
ChlamydiaRate                -0.044      0.001     -0.049     -0.043     -0.043
GraduationRate               -0.022      0.018     -0.050     -0.019      0.008
PercentSomeCollege            0.028      0.001      0.023      0.028      0.031
PercentSevereHousingProblems     -0.022      0.015     -0.082     -0.017     -0.008
AgeAdjustedMortality          0.005      0.003      0.004      0.005      0.033
PercentAdultsUninsured        0.071      0.002      0.069      0.070      0.094
HealthCareCosts               0.044      0.019      0.008      0.042      0.101
HouseholdIncome               0.069      0.007      0.040      0.067      0.085
5.1                          -0.014      0.003     -0.016     -0.014      0.016
PercentRural                 -0.026      0.004     -0.034     -0.026     -0.019
HealthBehaviorsRank          -0.011      0.001     -0.012     -0.011      0.001
HealthOutcomesRank            0.032      0.016      0.001      0.034      0.062
PercentAfricanAmerican       -1.447      0.001     -1.447     -1.447     -1.434
PercentAmericanIndianAlaskanNative     -0.883      0.137     -1.169     -0.865     -0.668
PercentAsian                 -0.321      0.001     -0.331     -0.321     -0.316
PercentNativeHawaiianOtherPacificIslander     -0.100      0.003     -0.107     -0.101
-0.082
PercentHispanic              -1.396      0.003     -1.408     -1.395     -1.393
PercentNonHispanicWhite      -2.137      0.154     -2.680     -2.139     -1.721
PercentUnder18FEM             0.008      0.001      0.007      0.008      0.012
Percent1824FEM               -0.010      0.001     -0.011     -0.011     -0.006
Percent2544FEM               -0.044      0.006     -0.054     -0.042     -0.035
Percent4564FEM               -0.072      0.002     -0.087     -0.071     -0.070
PercentOVER65FEM              0.036      0.001      0.035      0.036      0.041
T2DMPrevU                     0.123      0.268     -0.842      0.112      0.924
T2DMPrevO                    -0.047      0.003     -0.050     -0.048     -0.032
HypertensionPrevU            -0.028      0.001     -0.029     -0.028     -0.022
HypertensionPrevO             0.430      0.156     -0.139      0.451      0.890
OPPrevU                      -0.046      0.034     -0.115     -0.030      0.001
OPPrevO                       0.084      0.051      0.017      0.071      0.236
SZOthePsychdisdPrevU         -0.014      0.109     -0.276     -0.006      0.249
SZOthePsychdisdPrevO          0.228      0.062      0.060      0.241      0.423
===========================================================================
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