8-2023

Spatial Epidemiology of Prediabetes and Diabetes in Florida

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Spatial Epidemiology of Prediabetes and Diabetes in Florida

A Dissertation Presented for the

Doctor of Philosophy

Degree

The University of Tennessee, Knoxville

Md Marufuzzaman Khan

August 2023

DEDICATION

This dissertation is dedicated to my loving parents, Kamruzzaman and Hasina, for their unconditional love and constant support so that I could pursue my dream; to my elder brother, Hasan, who guided me in taking all important decisions of my life and taught me how to dream big.

ACKNOWLEDGEMENTS

I am so grateful to my mentor, Dr Agricola Odoi, for giving me the opportunity to learn and work under his supervision. I would like to thank my outstanding committee members, Dr Kristina Weis Kintziger, Dr Kathleen Conroy Brown, Dr Russell Lee Zaretzki, and people in the Department of Public Health for supporting my PhD journey in the US. I would also like to extend my gratitude to Dr Evah Wangui Odoi, Dr Jiangang Chen, Dr Brittany Shelton, and my colleagues in the Department of Comparative and Experimental Medicine for their unwavering support in fostering my academic and professional growth. Additionally, I am thankful to my friends and colleagues in Knoxville for making my time here memorable and enjoyable.

ABSTRACT

The burden of diabetes and diabetes-related Emergency Department (ED) visits has increased in Florida. However, Diabetes Self-management Education (DSME) Program participation remained considerably low. Little is known about disparities of DSME participation, diabetes complications, and ED use by diabetes patients in Florida and yet this information is important for guiding health programs aimed at reducing diabetes burden. Therefore, the objectives of this study were to investigate: (a) disparities of diabetes prevalence and DSME participation; (b) disparities of diabetes-related ED visit risks; and (c) prevalence and predictors of stroke among persons with prediabetes and diabetes.

Behavioral Risk Factor Surveillance System and ED data were obtained from the Florida Department of Health and the Agency for Healthcare Administration, respectively. Data were aggregated to the county level. Temporal changes of diabetes prevalence, DSME participation, and ED visit were investigated. High-risk spatial clusters were identified using Tango's flexible and Kulldorff's circular spatial scan statistics. Predictors of DSME participation, ED visit, and stroke were investigated using ordinary least square and logistic regression models. Geographic distribution of significant ($p \leq 0.05$) spatial clusters and predictors were displayed on maps.

There were significant ($p \leq 0.05$) increases in age-adjusted diabetes prevalence, DSME participation rates, and ED visit risks over time. Clusters of high diabetes prevalence and ED visit risks were identified in northern and central Florida, while clusters of high DSME participation rates were observed in central Florida. Rural counties and those with high proportions of Hispanic populations had low DSME participation rates. Counties with high proportions of populations that were Black, current smokers, uninsured, or with diabetes had significantly higher diabetes-related ED visit risks, while counties with high proportions of married individuals had significantly low ED visit risks. Individuals with prediabetes had high odds of strokes if they were ≥45 years old, had hypertension and hypercholesterolemia, while those with diabetes had high odds if they were non-Hispanic Black, hypertensive, and had depression.

The identified disparities and predictors of diabetes prevalence, DSME participation, diabetes-related ED visit, and stroke among populations with prediabetes and diabetes are useful in guiding evidence-based health planning and resource allocation in combating the diabetes problem in Florida.

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LIST OF ABBREVIATIONS

AHA= American Heart Association

ADA= American Diabetes Association

US= United States

BRFSS= Behavioral Risk Factor Surveillance System

FDOH= Florida Department of Health

CDC= Centers for Disease Control and Prevention

BMI= Body Mass Index

OR= Odds Ratio

CI= Confidence Interval

HDL= High Density Lipoprotein

LDL= Low Density Lipoprotein

TG= Triglyceride

FPG= Fasting Plasma Glucose

IGT= Impaired Glucose Tolerance

OGTT= Oral Glucose Tolerance Test

WHO= World Health Organization

IEC= International Expert Committee

IDF= International Diabetes Federation

NAC= North America and Caribbean

GDM= Gestation Diabetes Mellitus

BC-ADM= Board Certified in Advanced Diabetes Management

CDCES= Certified Diabetes Care and Education Specialists

NDEP= National Diabetes Educational Program

HHS= Department of Health and Human Services

NIH= National Institutes of Health

DSME= Diabetes Self-management Education

TIGER= Topologically Integrated Geographic Encoding and Referencing

FSSS= Flexible Spatial Scan Statistics

CSSS= Circular Spatial Scan Statistics

GIS= Geographic Information System

PRR= Participation Rate Ratio

OLS= Ordinary Least Square

VIF= Variance Inflation Factor

SE= Standard Error

DPP= Diabetes Preventive Program

ED= Emergency Department

ACSC= Ambulatory Care Sensitive Condition

ICD= International Classification of Diseases

FDOH= Florida Department of Health

CHHR= County Health Rankings and Roadmap

ACS= American Community Survey

LLR= Log Likelihood Ratio

CHAPTER 1

Introduction and Literature Review

1.1 Introduction

Diabetes and stroke are the seventh and fifth leading causes of death in the US, respectively (Centers for Disease Control and Prevention, 2020a, 2020d). The burden of diabetes has been increasing in Florida as evidenced by the fact that diabetes prevalence has increased from 5.2% in 1995 to 11.8% in 2016 (Florida Diabetes Advisory Council, 2019). In addition, almost 9.4% of adults in Florida have prediabetes (Florida Diabetes Advisory Council, 2019; Zhang et al., 2010). Individuals with prediabetes have a 5-20 times higher risk of developing diabetes compared to those who don’t have prediabetes (Florida Diabetes Advisory Council, 2019; Zhang et al., 2010). Moreover, diabetes is a risk factor for several chronic conditions such as kidney disease, heart attack, and stroke. In Florida, 25.8% of adults with diabetes had a history of heart attack, coronary heart disease, or stroke, compared to 7.7% of adults without diabetes (Florida Diabetes Advisory Council, 2019). There is evidence that about 23-53% of stroke patients have prediabetes (Fonville et al., 2014; Mijajlovic et al., 2017). Understanding the epidemiology of stroke among individuals with diabetes and prediabetes is important in guiding evidence-based health planning and preventive/control strategies.

The Diabetes Self-Management Education (DSME) program is an evidence-based program recommended for reducing diabetes-related complications and improving clinical outcomes (Brunisholz et al., 2014). However, it is unclear whether all communities across Florida have benefitted from DSME equitably. There is evidence that poor diabetes management leads to unnecessary/preventable Emergency Department (ED) visits and subsequent hospitalizations of diabetes patients. The increases in diabetes-related ED visits (54%) and hospitalizations (16%) in Florida between 2011 and 2016 imply growing diabetes management problems (Florida Diabetes Advisory Council, 2019). I hypothesize that there are geographic disparities in DSME participation rates and ED visits that if identified would be used to guide efforts to address the problem and improve diabetes outcomes. Identifying areas with unusually high diabetes prevalence and diabetes-related ED visits but low DSME participation rates is crucial for guiding planning to improve access to diabetes care and reduce disparities in diabetes outcomes. Therefore, the aims of this study are to: 1) investigate geographic disparities and temporal changes of diabetes prevalence, DSME participation rates, and predictors of disparities in DSME participation rates in Florida; 2) identify geographic disparities and temporal changes in diabetes-related ED visits and sociodemographic determinants of the identified disparities in Florida; 3) estimate the prevalence and identify risk factors of stroke among persons with prediabetes and diabetes in Florida.

1.2 Literature Review

1.2.1 Prediabetes and Diabetes

1.2.1.1 Etiology

Prediabetes can be defined as an intermediate hyperglycemic condition in which blood glucose levels are higher than normal but not high enough to be diagnosed as diabetes (Fasting Plasma Glucose [FPG]: 100-<126 mg/dl) (American Diabetes Association, 2020; Mayo Clinic, 2022b; National Institute of Diabetes and Digestive and Kidney Diseases, 2018). Individuals with prediabetes cannot process blood glucose properly. This could be due to either a deficiency in insulin or insulin resistance. Insulin is a hormone produced by the β-cells of the pancreas and used to transport glucose from the bloodstream into the cells and help maintain a normal blood glucose level. Therefore, the lack of insulin or the body's inability to utilize insulin results in hyperglycemia (Mayo Clinic, 2022b; National Institute of Diabetes and Digestive and Kidney Diseases, 2018).

Diabetes is a chronic metabolic condition characterized by FPG levels of ≥126 mg/dl (American Diabetes Association, 2020). The etiology of diabetes depends on the type. Diabetes can be classified into three primary types: type 1, type 2, and gestational or pregnancy-related diabetes (Centers for Disease Control and Prevention, 2022c). A small number of people develop diabetes due to other causes (American Diabetes Association, 2023a): (a) Monogenic diabetes syndromes, such as neonatal onset or maturity-onset diabetes of the young; (b)

Diseases of the exocrine pancreas, such as cystic fibrosis and pancreatitis; (c) Drug or chemical induced diabetes, such as glucocorticoid, anti-seizure, or psychiatric drugs. In type 1 diabetes, the body is unable to produce insulin due to the autoimmune destruction of insulin-producing β-cells (Centers for Disease Control and Prevention, 2022a). The etiology of type 2 diabetes is similar to that of prediabetes, but the condition is more severe, resulting in excessively high blood glucose levels. About 90-95% of people with diabetes have this type, which is usually common in adults. The exact etiologies of gestational diabetes are unknown, however, insulin resistance due to placental hormones could be a reason (National Institute of Diabetes and Digestive and Kidney Diseases, 2022a).

1.2.1.2 Symptoms

Individuals with prediabetes usually do not show any symptoms (Mayo Clinic, 2022b). However, evidence suggests that some people with prediabetes may develop acanthosis nigricans and skin tags (Mayo Clinic, 2022b; National Institute of Diabetes and Digestive and Kidney Diseases, 2018). Acanthosis nigricans is a condition in which the skin in the armpit, on the back, or sides of the neck becomes darker (Mayo Clinic, 2022b; National Institute of Diabetes and Digestive and Kidney Diseases, 2018). People with prediabetes may share some of the classic symptoms of diabetes (Mayo Clinic, 2022b), which are increased thirst, frequent urination, increased hunger, fatigue, blurred vision, numbness or tingling in the feet or hands, delayed sore healing or failure of sore healing, and unexplained weight loss (National Institute of Diabetes and Digestive and Kidney Diseases, 2016b). The onset of these symptoms depends on the blood glucose level. Individuals with type 1 diabetes may present symptoms early, while individuals with type 2 diabetes sometimes have no symptoms until cardiovascular complications, such as heart attack or stroke, develop (Centers for Disease Control and Prevention, 2022n; National Institute of Diabetes and Digestive and Kidney Diseases, 2016b).

1.2.1.3 Diagnostic Criteria

There is no widely accepted single criteria or definition for diagnosing prediabetes. Currently, five different definitions of prediabetes have been proposed by professional societies and used in clinical settings worldwide. The American Diabetes Association (ADA) issued the following three definitions of prediabetes: (1) Impaired Fasting Glucose (IFG): FPG level of 100-125 mg/dl; (2) Impaired Glucose Tolerance (IGT): 2-hour Post load Blood Glucose (2-HBG) level of 140-199 mg/dl in the 75-g Oral Glucose Tolerance Test (OGTT); and (3) Hemoglobin (Hb) A1c level of 5.7-6.4%. The World Health Organization (WHO) considered a slightly higher FPG level for prediabetes and provided the fourth definition, WHO-IFG (FPG of 110-125 mg/dl). However, the WHO accepted the ADA’s IGT definition and did not acknowledge the HbA1c definition for prediabetes. Finally, the International Expert Committee (IEC) presented the fifth definition of prediabetes based on the HbA1c range of 6-6.4%. These variations in diagnostic criteria/definitions present a considerable challenge to estimating the global burden of prediabetes (Echouffo-Tcheugui & Selvin, 2021).

Unlike prediabetes, universal diagnostic criteria are available for diabetes. According to the recommendations of the WHO, ADA, and International Diabetes Federation (IDF), diagnosis of diabetes occurs if one or more of the following criteria are met: FPG ≥ 126 mg/dl; 2-HBG ≥ 200 mg/dl; Random Plasma Glucose (RPG) ≥ 200 mg/dl; or HbA1c ≥ 6.5% (American Diabetes Association, 2023b; International Diabetes Federation, 2021).

1.2.1.4 Treatment

Maintaining a healthy lifestyle is the key to managing prediabetes and reducing the risk of developing type 2 diabetes (Mayo Clinic, 2022b). Appropriate use of medications and lifestyle change programs could even reverse hyperglycemic condition of prediabetes to normoglycemic condition (National Institute of Diabetes and Digestive and Kidney Diseases, 2018). Evidence suggests that losing 7% of total body weight and doing moderate exercises, such as brisk walking for 30 minutes a day and five days a week, could reduce the risk of developing diabetes by up to 58% (American Diabetes Association, 2023b; Mayo Clinic, 2022a). Several educational programs are available in the US to help individuals with prediabetes in learning ways of living a healthy life. The Centers for Disease Control and Prevention (CDC) offers a year-long evidence-based lifestyle change program known as the National Diabetes Prevention Program (NDPP). It is a structured in-person or online program designed for populations with prediabetes to help adopt healthy habits, such as eating healthier, reducing stress, and being more physically active. Additionally, several online diabetes prevention programs and personal coaching are available and acknowledged by the CDC (Centers for Disease Control and Prevention, 2022m).

Although no medication is currently approved for prediabetes, metformin has been used as an "Off-level" drug for managing the condition. Metformin, a first-line medication for obese patients with diabetes, is effective in delaying the onset of diabetes among patients with prediabetes. Similarly, Glucagon-like Peptide 1 (GLP-1) receptor agonist, another approved drug for obesity management, could be used for prediabetes. Current ADA recommendations for prediabetes management include: a) Referral to a lifestyle change program like the DPP; b) Annual checkup for diabetes; and c) Use of metformin if Body Mass Index (BMI) ≥35 kg/m2, age less than 60 years, and women with prior history of GDM (American Diabetes Association, 2021a).

Although there is currently no cure for diabetes, the condition can be effectively managed through diet and lifestyle modifications and the appropriate use of medications. There are four main aspects of diabetes management: Regular monitoring of blood sugar, diet, exercise, and Oral medications and insulin (Cleveland Clinic, 2023).

1.2.1.4.1 Regular Monitoring of Blood Sugar

Monitoring blood sugar is essential for tracking the progress of treatment and modifying diabetes management plan to achieve persistent normoglycemic condition. Blood sugar can be measured using a glucometer and finger stick or a continuous glucose monitor device.

1.2.1.4.2 Diet

Diabetes patients could eat different types of healthy foods from a variety of food groups described below (National Institute of Diabetes and Digestive and Kidney Diseases, 2016a):

1. Vegetables:
    - I. Non-starchy, such as broccoli, carrots, and tomatoes.
    - II. Starchy, such as potatoes, corn, and green peas.
2. Fruits include oranges, barries, melon, apples, bananas, and grapes.
3. Grains include rice, wheat, oats, barley, and quinoa. At least half of the grains should be whole grains.
4. Protein, such as lean meat, chicken, fish, eggs, nuts and peanuts (avoid if allergic), dried beans, and meat substitutes like tofu.
5. Nonfat or low-fat dairy, such as milk or lactose free milk, yogurt, and cheese.

6. Heart healthy foods include canola and olive oil, nuts and seeds, avocado, and fish, such as salmon, tuna, and mackerel.

Although diabetes patients could eat different types of foods, they should limit taking the following foods:

1. Fried foods high in saturated and trans-fat.
2. Foods high in salt (sodium).
3. Sweets, such as baked goods, candy, and ice-cream.
4. Beverages with added sugars including cold drinks, juices, and energy/sports drinks.

Since the types of foods consumed can affect blood glucose levels, a diet plan is a crucial aspect of diabetes management. Diabetes patients must take food in a controlled amount following the dietary plan provided by their healthcare providers. This is more important for people with diabetes who take insulin as a part of their treatment plan. The amount of carbohydrates in the diet determines the required insulin level. In addition, following a dietary plan could help control weight and reduce complications. The dietary plan is usually constructed based on either the carb counting or the plate method. In the carb counting method, the meal plan is designed based on carbs measured in grams. On the other hand, the plate method is simpler and includes filling half of the plate with non-starchy vegetables, a quarter with a lean protein, and the rest with carb foods (Centers for Disease Control and Prevention, 2022j). However, healthcare providers decide the dietary plan and method for diabetes patient based on age, weight, activity level, and other health related factors. Individuals with diabetes are also suggested to take plain drinking water and consider using sugar substitutes in coffee or tea.

1.2.1.4.3 Exercise

Regular physical activity can greatly help manage diabetes because exercise increases insulin sensitivity and reduces resistance. According to the CDC, diabetes patients should do moderate intensity physical activity for at least 150 minutes per weak, or at least 20 to 25 minutes of activity every day (Centers for Disease Control and Prevention, 2022k). Moderate intensity physical activities include doing household work, brisk walking, swimming, bicycling, lawn-mowing, and playing sports.

1.2.1.4.4 Oral Medications and Insulin

Several types of medications, such as metformin, glinides, gliptins, acarbose/miglitol, and sulfonylureas (glipizide), are used to manage type 2 diabetes (Cleveland Clinic, 2022). However, medications are effective when at least a minimum amount of insulin is produced. Therefore, taking exogenous synthetic insulin is the only way of treatment for type 1 diabetes. Some people with type 2 diabetes may require insulin in the long run. Different types of insulin are available, such as rapid-acting, short-acting, regular, intermediate-acting, and long-acting. There are four types of insulin based on administration process: injectable insulin using a syringe, insulin pens, insulin pumps, and rapid-acting inhaled insulin (Centers for Disease Control and Prevention, 2022p).

1.2.1.5 Burden of Prediabetes and Diabetes

The estimation of global prediabetes prevalence depends on the definitions of prediabetes used. According to the report published by the IDF 10th edition, the global prevalence of prediabetes based on the IGT definition was 10.6% (541 million) of total adult populations aged 20-79 years old in 2021 (International Diabetes Federation, 2021). However, based on the WHO-IFG definition, 319 million adults, or 6.2% of the global adult population, had prediabetes. On the other hand, 10.5% (537 million) of adults in the same age group had diabetes worldwide in 2021, which included type 1, type 2, undiagnosed, and diagnosed diabetes (International Diabetes Federation, 2021). Diabetes is one of the most expensive chronic conditions, accounting for 11.5% of global health spending (International Diabetes Federation, 2021). This expenditure increased 316% over 15 years, from $232 billion in 2007 to $966 billion in 2021. The IDF estimates that total diabetes-related health expenditure will reach $1.03 trillion by 2030 (International Diabetes Federation, 2021).

According to the IDF report, 47 million people, or 11.2% of the total adult population aged 20-79 years old, have prediabetes defined by the IGT definition in countries in the North America and Caribbean (NAC) region, including the US, in 2021 (International Diabetes Federation, 2021). Similar to global prevalence, the WHO-IFG definition estimated a lower prediabetes prevalence in the NAC region (31.6 million or 8.3% of total adults) (International Diabetes Federation, 2021). However, the CDC used the ADA definitions and reported different prevalence estimates of prediabetes in the US. According to the CDC report, 38.0% of all US adults (approximately 96 million) had prediabetes, based on their ADA-IFG or HbA1C levels. It indicates that more than 1 in 3 persons in the US have prediabetes. Surprisingly, 80% of these populations with prediabetes do not know that they have the condition (Centers for Disease Control and Prevention, 2022o). In total, 37.1 million adults, or 14.7% of the US adult population, had diabetes. Approximately 23% of all US adults with diabetes were undiagnosed. Diabetes is a costly disease as evidenced by the fact that people with diagnosed diabetes had 2.3 times higher medical costs than those without diabetes. In 2017, the total diabetes-related medical expenditure in the US was about $404 billion, of which $327.2 billion was spent on providing care for people with diagnosed diabetes, $43.4 billion was attributed to prediabetes care, and the rest was used for people with undiagnosed diabetes and GDM (Dall et al., 2019). On average, every $1 out of $4 of the US medical cost was spent on providing healthcare to individuals with diabetes (Centers for Disease Control and Prevention, 2022l).

Florida is located in the diabetes belt, a region in the southeastern US where diabetes prevalence is significantly higher compared to the rest of the country (Barker et al., 2011). According to the ADA report published in 2021, 35.7% of the adult population (approximately 6 million) in Florida had prediabetes, while 12.5% of the adult or 2.1 million people had been diagnosed with diabetes (American Diabetes Association, 2021b). Florida also has a high burden of diabetes-related expenditures. In 2017, the total estimated cost of diabetes in Florida was $25 billion, including $19.3 billion as direct medical costs for diagnosed and undiagnosed diabetes, prediabetes, and gestational diabetes, and $5.5 billion as indirect costs for disability due to the disease (American Diabetes Association, 2021b).

1.2.1.6 Geographic Patterns of Prediabetes and Diabetes

The geographic distribution of prediabetes varies depending on the definition used to identify populations with the condition. According to the IDF's report, the age-adjusted prevalence of prediabetes based on IGT was highest in the Western Pacific region (12.9%), including Australia and China, and lowest in the Southeast region (5.4%), including India and Bangladesh, in 2021 (International Diabetes Federation, 2021). However, age-adjusted prediabetes prevalence defined by the WHO-IFG definition was lowest in countries of the Western Pacific (2.5%), and highest in South and Central America (10.0%). Overall, low-income countries had the highest prevalence of IGT (12.7%), while the WHO-IFG prevalence was almost similar among high, middle, and low-income countries in 2021 (International Diabetes Federation, 2021). In contrast, the highest diabetes prevalence was reported in middle-income countries (10.5%) in the same year. Globally, people with diabetes tend to live in urban areas. Based on regions, the highest age-adjusted diabetes prevalence was reported among populations in the Middle East (18.1%), while the lowest was in North Africa (5.3%). This could be due to the fact that countries in North Africa were mostly rural and had a low prevalence of overweight and obesity (International Diabetes Federation, 2021). Although China had the highest number of populations with diabetes (140.9 million), the highest diabetes prevalence was reported in Pakistan (30.8%) (International Diabetes Federation, 2021).

Little information is available on the geographic distribution of prediabetes in the US. However, a study by Lee et al. reported that the prevalence of prediabetes and diabetes was higher in the stroke belt region than in other parts of the US (L. T. Lee et al., 2014). The stroke belt includes states of the southeast part of the US: North Carolina, South Carolina, Georgia, Alabama, Mississippi, Tennessee, Louisiana, and Arkansas. The areas in the Stroke belt had age-adjusted stroke mortality at least 10% above the national average (L. T. Lee et al., 2014). This belt also overlaps with the diabetes belt identified by Barker and co-workers (Barker et al., 2011). The diabetes belt is an area where diabetes prevalence is significantly higher (11.7%) than the US national average (8.5%). The diabetes belt included the following states of the southeast region: Arkansas, Florida, Kentucky, Mississippi, Georgia, North Carolina, Ohio, Pennsylvania, South Carolina, Louisiana, Alabama, Tennessee, Virginia, West Virginia, and Texas (Barker et al., 2011). The reason for the higher diabetes prevalence in these area could be geographical differences in distributions of modifiable lifestyle factors and non-modifiable genetic factors (Barker et al., 2011).

Counties located in the north-central part of Florida had a higher prevalence of both prediabetes and diabetes than the rest of the state (Lord et al., 2020). A similar pattern of distribution was reported in a study by Shrestha et at., which also identified significant county-level predictors of diabetes prevalence in Florida. These predictors were: higher percentages of populations living in poverty, non-Hispanic Black, obesity, and physical inactivity (Shrestha, 2012). Additionally, high diabetes prevalence was reported in a few counties located in the south-central part of Florida (Lord et al., 2020).

1.2.1.7 Temporal Trends of Prediabetes and Diabetes

The prevalence of prediabetes has been increasing globally over time among adults aged 20-79 years old irrespective of the definitions used. It has been projected that the worldwide age-adjusted prevalence of IGT will be 11.4% of all adults (730 million) and WHO-IFG will reach 6.9% of all adults (441 million) by 2045 (International Diabetes Federation, 2021). Interestingly, the age-adjusted prevalence of prediabetes based on the ADA-IFG or HbA1c criteria among adults aged 18 years or older has remained relatively stable in the US from 2005 to 2020 (Centers for Disease Control and Prevention, 2022h). However, a significant ($p \leq 0.05$) increasing trend of prediabetes was reported among US youths aged 12-19 years from 1999 to 2018 (Liu et al., 2022). Additionally, prediabetes awareness increased by 17.4% in the US during this period (Centers for Disease Control and Prevention, 2022h). Unlike the overall stable trend of prediabetes observed in the US, an increasing trend of prediabetes prevalence was reported among Florida adults. A study by Lord et al. reported that the state-wide age-adjusted prevalence of prediabetes in Florida increased significantly ($p \leq 0.05$) from 8.0% in 2013 to 10.5% in 2016 (Lord et al., 2020).

Similar to the global trend observed in prediabetes prevalence, the total number of individuals with diabetes, including type 1, type 2, undiagnosed, and diagnosed diabetes, is estimated to increase worldwide by 46% from 537 million adults in 2021 to 783 million adults in 2045 (International Diabetes Federation, 2021). The greatest percentage increase will be observed among populations of middle-income countries. Unlike prediabetes prevalence, diabetes prevalence among adults aged 18 years or older in the US has been steadily increasing from the time period of 2001-2004 to 2017-2020 across all age groups, races and ethnicities, sexes, and education levels (Centers for Disease Control and Prevention, 2022g). However, diabetes incidence has been decreasing from 2009 to 2019 (Centers for Disease Control and Prevention, 2022f). Therefore, the observed growing trend of diabetes prevalence could be due to the fact that people with diabetes are living longer because of improved healthcare services and the implementation of different educational and lifestyle change programs. The number of patients with diabetes has doubled over the past 20 years in the US and is estimated to double or triple again by 2050 (Centers for Disease Control and Prevention, 2010). Similarly, the prevalence of diabetes among Florida adults has been growing over the past 20 years. Diabetes prevalence in Florida more than doubled from 5.2% in 1995 to 12.6% in 2018 (Florida Department of Health, 2017).

1.2.1.8 Risk Factors of Prediabetes and Diabetes

Both prediabetes and diabetes share several risk factors described below:

1.2.1.8.1 Lifestyle-related Factors

Individuals who are overweight (BMI>25 kg/m2) or obese (BMI>30 kg/m2) have significantly higher risks of developing prediabetes and diabetes than those who have normal weight (Echouffo-Tcheugui & Selvin, 2021; National Institute of Diabetes and Digestive and Kidney Diseases, 2022b). A study reported that more than 80% of individuals with self-reported prediabetes were overweight or obese (Echouffo-Tcheugui & Selvin, 2021). Similarly, insulin resistance is significantly ($p \leq 0.05$) associated with a larger waist size. The risk of prediabetes and diabetes increases for men with waists larger than 40 inches and for women with waists larger than 35 inches, even if their BMIs fall in the normal range (Echouffo-Tcheugui & Selvin, 2021; National Institute of Diabetes and Digestive and Kidney Diseases, 2022b). Specific diet patterns such as eating red and processed meat and drinking sugar-sweetened beverages are associated with a higher risk of both conditions (Mayo Clinic, 2022b). Inadequate physical exercise is also linked with obesity and insulin resistance. People who are not physically active because of physical limitations, a sedentary lifestyle, or a job that requires sitting for long periods are at greater risk of prediabetes and diabetes (National Institute of Diabetes and Digestive and Kidney Diseases, 2022b). These lifestyle-related factors are modifiable risk factors that could be controlled by leading a healthy lifestyle.

1.2.1.8.2 Medical Conditions (Co-morbidities)

Certain medical conditions, such as high blood pressure and abnormal cholesterol level (low level of high-density lipoprotein cholesterol and high level of triglycerides), are associated with higher risk for prediabetes and diabetes (Okwechime et al., 2015). Previous history of certain diseases, such as gestational diabetes (GDM), heart disease, stroke, and polycystic ovarian syndrome, is strongly associated with both conditions (Echouffo-Tcheugui & Selvin, 2021; National Institute of Diabetes and Digestive and Kidney Diseases, 2022b). Additionally, sleep apnea, certain medications, such as glucocorticoid, several antipsychotics and HIV drugs, hormonal disorders, such as Cushing's syndrome and Acromegaly could increase risks for insulin resistance and development of prediabetes and diabetes (Echouffo-Tcheugui & Selvin, 2021; National Institute of Diabetes and Digestive and Kidney Diseases, 2022b). It is worth noting that prediabetes itself is a strong risk factor for type 2 diabetes (Okwechime et al., 2015).

1.2.1.8.3 Genetic and Familial Factors

Individuals with a parent or sibling that have diabetes are at a higher risk of prediabetes and diabetes (Okwechime et al., 2015). Although risk factors for type 1 diabetes are not as evident as for prediabetes and type 2 diabetes, genetic and familial history is supposed to be one of the most important risk factors of type 1 diabetes (Centers for Disease Control and Prevention, 2022n).

1.2.1.8.4 Sociodemographic Characteristics

Although prediabetes and diabetes can develop at any age, the risk of these metabolic conditions increases with age, especially after 45 years (Centers for Disease Control and Prevention, 2022a). According to the report published by the CDC, the prevalence of prediabetes identified using the ADA-IFG or HbA1c was 27.8% in adults aged 20-44 years old and 48.8% in adults ≥65 years old in the US (Centers for Disease Control and Prevention, 2022h). Several studies reported that older age was significantly associated with a higher risk of prediabetes and diabetes compared to younger age groups (Centers for Disease Control and Prevention, 2022a; Echouffo-Tcheugui & Selvin, 2021; Hilawe et al., 2016; Zhu et al., 2019).

Age-standardized prevalence of prediabetes was higher among men than women (36.5% [36.4–36.7%] vs. 31.0% [30.9–31.1%]) (Martins et al., 2017; Zhu et al., 2019). However, a study by Okwechime et al. did not identify age, race, and gender as significant predictors of prediabetes (Okwechime et al., 2015). Additionally, a recent report by the CDC showed that prediabetes prevalence was almost similar among all racial and ethnic groups (Centers for Disease Control and Prevention, 2022h). Therefore, demographic profiles may differ among populations with prediabetes due to the use of different definitions. For example, people with prediabetes identified by HbA1c were more likely to be older, female, Black, and obese than people with prediabetes determined by the ADA-IFG or IGT definitions of prediabetes (Ali et al., 2018; Rhee et al., 2010; Warren et al., 2017). However, age-adjusted diabetes prevalence and incidence did not vary significantly by sex (Centers for Disease Control and Prevention, 2022g).

High age-adjusted diabetes prevalence was reported among populations with less than high school education (13.4%) compared to those with high school education (9.2%) and more than high school education (7.1%). Individuals who fall below the federal poverty limit also tend to have high age-adjusted diabetes prevalence (Centers for Disease Control and Prevention, 2022g). Racial and ethnic minorities such as non-Hispanic Black, Hispanic, American Indian, and Asian American have high risks of prediabetes and diabetes, even at low BMI (Mayo Clinic, 2022b, 2022c; Zhu et al., 2019). This is probably due to the higher prevalence of inherent genetic risk factors, low socioeconomic conditions, and unhealthy lifestyles among these populations (Zhu et al., 2019).

1.2.1.9 Complications of Prediabetes and Diabetes

The most obvious complication of prediabetes is the increased risk of developing type 2 diabetes over time. According to the report published by CDC, 15-30% of individuals with prediabetes will develop type 2 diabetes in 5 years if no actions are taken (Centers for Disease Control and Prevention, 2023; New York State Department of Health, 2023). Prediabetes is strongly associated with long-term damage to the heart, blood vessels, and kidneys, even after excluding subsequent progression to diabetes and adjusting for metabolic factors (Mayo Clinic, 2022a; Zhang et al., 2023). However, individuals with prediabetes are more likely to present these complications in the long run.

High blood glucose levels in diabetes can affect many organ systems of the body and produce a vast array of complications. These complications are of two types: acute or short-term and long-term complications. Short-term complications include severe hypoglycemia (low blood sugar), hyperosmolar hyperglycemic state (HHS), and diabetes-related ketoacidosis (DKA). The condition of DKA is more common in people with type 1 diabetes, while individuals with type 2 diabetes tend to have HHS (Cleveland Clinic, 2023). Long-term complications of diabetes include (Cleveland Clinic, 2023): cardiovascular diseases, such as high blood pressure, high blood cholesterol, coronary artery diseases, atherosclerosis, stroke, and heart attack; neuropathy, such as numbness, tingling, or pain; retinopathy or blurred vision; nephropathy, and chronic kidney diseases; diabetic foot; amputations of lower limbs; skin infections; sexual dysfunction; gastroparesis; fatty liver; hearing loss; oral health problems, such as gum disease. Cardiovascular diseases are the most common complications among patients with any type of diabetes.

1.2.1.9.1 Stroke among Populations with Prediabetes or Diabetes

Stroke is one of the most common complications of diabetes resulting from persistent high blood glucose levels. Stroke occurs when there is a lack of blood supply to a part of the brain due to either blockage of a vessel from a blood clot (ischemic stroke) or bleeding from a ruptured vessel (hemorrhagic stroke) (American Stroke Association, 2021a). It is the 5th leading cause of death in the

US and more than 600,000 people in the country experience first time stroke each year (Centers for Disease Control and Prevention, 2020a, 2020d). It is also the leading cause of long-term disability and costs $34 billion annually in the US (Centers for Disease Control and Prevention, 2020d).

Both prediabetes and diabetes are major risk factors for stroke. Individuals with diabetes have two times higher risk of experiencing a stroke than those that do not have the condition (American Stroke Association, 2021b). Prediabetes, on the other hand, is a modest risk factor for first-time stroke but doubles the risk of recurrent stroke (Fonville et al., 2014; M. Lee et al., 2012). There is evidence that about 23-53% of stroke patients have prediabetes, while 14-46% have diabetes (Fonville et al., 2014; Mijajlovic et al., 2017). The increasing trends in prediabetes and diabetes prevalence will likely result in increases of stroke burden in the future. However, not much is known about the epidemiology of stroke in these populations because previous studies have mainly focused on investigating the epidemiology of stroke in the general population (Boehme et al., 2017).

The burden of diabetes has been increasing in Florida as evidenced by the fact that diabetes prevalence has increased from 5.2% in 1995 to 12.6% in 2018 (Florida Diabetes Advisory Council, 2019). Florida also has a high burden of prediabetes. Almost 35.7% of the adult population (approximately 6 million) in Florida had prediabetes in 2021 (American Diabetes Association, 2021b). This increase will likely result in an increase of Florida's stroke burden. However, limited information is available on the prevalence and predictors of stroke among populations with prediabetes and diabetes in Florida. Understanding stroke epidemiology among individuals with prediabetes and diabetes is important for guiding evidence-based health planning and service provision to control stroke burden and improve quality of care for stroke patients.

1.2.2 Diabetes Education Programs

The findings of the Diabetes Control and Complications Trial (DCCT) and the UK Prospective Diabetes Study (UKPDS) recommended that maintaining normal blood glucose levels is the key to reducing complications of type 1 and type 2 diabetes (Nathan et al., 1993; UK Prospective Diabetes Study Group, 1998). In order to implement this recommendation in clinical and public health settings, the US Department of Health and Human Services (DHHS), the National Institutes of Health (NIH), and the CDC jointly launched the National Diabetes Education Program (NDEP in 1997 (Siminerio et al., 2018). Over time, the NDEP developed various educational resources and programs, such as the Diabetes Self-management Education Program (DSME), aimed at teaching individuals with diabetes and their family members to manage the condition, while also encouraging healthcare providers to adopt patient-centered approaches and team-based care in diabetes management practices (Clark et al., 2000). Later in 2002, a study conducted in the US showed that lifestyle intervention program is also effective in preventing or delaying the incidence of type 2 diabetes among populations with prediabetes (Knowler et al., 2002). Based on this finding, the NDEP helped to develop and expand the National Diabetes Prevention Program (NDPP) in communities across the US (Siminerio et al., 2018). At present, the CDC recommends the NDPP for people with prediabetes to delay progression of prediabetes to diabetes, while the DSME is recommended for people with diabetes to reduce complications and improve quality of life (Centers for Disease Control and Prevention, 2022i, 2022m).

1.2.2.1 Diabetes Self-management Education (DSME) program

According to the joint statement of the ADA, the American Association of Diabetes Educators (AADE), and the Academy of Nutrition and Dietetics (AND), DSME program is “the active, ongoing process of facilitating the knowledge, skill, and ability necessary for diabetes self-care” (Powers et al., 2016). This program is designed to “address the patient’s health beliefs, cultural needs, current knowledge, physical limitations, emotional concerns, family support, financial status, medical history, health literacy, numeracy, and other factors that influence each person’s ability to meet the challenges of self-management” (Powers et al., 2016).

Traditionally, diabetes education was provided by registered nurses and dietitians. However, today’s DSME programs involve a multidisciplinary team consisting of a diabetes educator and other healthcare professionals (Centers for Disease Control and Prevention, 2021a, 2022d). These diabetes educators may be from various professional backgrounds, such as registered nurses, dietitians, pharmacists, or other healthcare professionals with specialized certifications provided by the Board Certified in Advanced Diabetes Management (BCADM) and the Certified Diabetes Care and Education Specialists (CDCES). Additionally, the team may include physicians, mental health specialists, certified health education specialists, exercise physiologists, and other specialty providers (Centers for Disease Control and Prevention, 2021a, 2022d; Davis et al., 2022). Furthermore, health workers such as diabetes community care coordinators, community health workers, health promoters, dietetic technicians, and social workers can support people with diabetes as a part of the team with appropriate training and supervision. This multidisciplinary patient-centered approach makes it possible to deliver DSME in:

a) many traditional healthcare settings (such as outpatient departments, rural clinics, pharmacies, independent clinics, public health departments, skilled nursing homes), and
b) alternative settings (including community-based organizations, community centers, faith-based organizations, etc).

Other benefits of the multidisciplinary approach include access to multiple experts, increased patient follow-up, greater patient satisfaction, better glycemic control, and reduced hospitalizations (Centers for Disease Control and Prevention, 2021a, 2022d; Davis et al., 2022).

1.2.2.1.1 Benefits of DSME Program

Evidence shows that DSME is cost-effective and results in lowering the risk of diabetes-related complications and reducing hospital admissions and readmissions (Centers for Disease Control and Prevention, 2022e; Duncan et al., 2009; Norris et al., 2002; Powers et al., 2016; Steinsbekk et al., 2012). For individuals with type 2 diabetes, participating in DSME has been found to decrease their HbA1c levels, improve control of blood pressure and cholesterol, increase medication adherence rates, and encourage healthier lifestyle behaviors, such as engaging in more physical activity, adopting better dietary habits, and making greater use of primary and preventive care services. Participating in DSME can also enhance self-efficacy and empowerment, promote healthy coping mechanisms, and decrease diabetes-related distress and depression (Centers for Disease Control and Prevention, 2022e; Powers et al., 2016). Additionally, the amount of time spent with a diabetes educator is reported to be associated with better outcomes for people with diabetes (Duncan et al., 2009; Norris et al., 2002; Steinsbekk et al., 2012).

1.2.2.1.2 Geographic Disparities and Temporal Patterns of DSME Program Participation

Although the burden of diabetes has increased over time, DSME participation rate has remained consistently low in the US (Centers for Disease Control and Prevention, 2018a). Only about 54.4% of the population with diabetes attended a DSME program in 2015. The DSME program had the lowest participation rate compared to all the other diabetes-related preventive programs recommended by the CDC (Centers for Disease Control and Prevention, 2018a). The rate was even lower among populations with newly diagnosed diabetes (<7%) and Medicare participants (4%) (Li et al., 2014). In addition, significant geographic disparities were observed in DSME program availability across the US. Only 39.8% of the US counties had at least one DSME program accredited by the ADA (Rutledge et al., 2017). A study by Li et al. reported that DSME participation rates among populations residing in non-metropolitan areas were significantly lower than those in metropolitan areas (Li et al., 2014). Study findings also showed that the southern part of the US had higher diabetes prevalence but the lowest DSME participation rate compared to other regions (Li et al., 2014). This was probably due to the fact that these areas were mostly rural and had the lowest number of DSME program locations (Paul et al., 2018). Another study by Rutledge et al. reported that 62% of non-metropolitan countries in the US did not have a single DSME program in 2016. Rural and socially disadvantaged areas were less likely to have DSME programs than urban areas (Rutledge et al., 2017).

1.2.2.1.3 Barriers to DSME Program Availability and Accessibility

A complex array of individual/patient, county, and program-level factors influence availability and access to DSME programs and hence participation rates (Balamurugan et al., 2006; Y.-H. Lee, 2020; Powell et al., 2005; Testerman & Chase, 2018). These factors are discussed below.

1.2.2.1.3.1 Individual/Patient Level Barriers

Diabetes Self-management Education (DSME) participation are influenced by individuals' socioeconomic, demographic, cultural, and behavioral factors. Therefore, DSME program design/implementation should consider community and regional demographic characteristics such as ethnic/cultural background, age, sex, levels of education, and literacy to increase participation (Fain, 2017). A study among the Hispanic/Latino population identified male participants' shame of illness and lack of interest in health as significant predictors of low DSME class attendance (Testerman & Chase, 2018). Other individual-level barriers include lack of time (Testerman & Chase, 2018), language barriers (Testerman & Chase, 2018), lack of transportation (Balamurugan et al., 2006; Testerman & Chase, 2018), health insurance shortfalls (Davis et al., 2022), lack of childcare (Testerman & Chase, 2018), noncompliance with care, and lack of family support

(Powell et al., 2005). Behavioral factors such as perceived lack of need, awareness and willingness to participate, and little encouragement from healthcare professionals could be responsible for low DSME participation rates (Balamurugan et al., 2006; Davis et al., 2022).

1.2.2.1.3.2 County Level Barriers

Previous studies identified significant associations between county-level factors and DSME program availability (Rutledge et al., 2017). Rural areas tended to have fewer DSME programs across the US (Rutledge et al., 2017). In addition, counties with high diabetes prevalence and high percentages of insured population tended to have a DSME program, while counties with high percentages of individuals with a high school education or less and high unemployment rates were less likely to have any DSME program (Paul et al., 2018). These factors are closely related to the county-level socioeconomic factors.

1.2.2.1.3.3 Program Level Barriers

The following program-level barriers have been identified (Balamurugan et al., 2006): (a) Lack of sites for delivering programs; (b) Limited funding; (c) Delayed or insufficient insurance reimbursement; (d) Shortage of staff, such as qualified diabetes educators; (e) Requirement for physician referrals for DSME participation; and (f) Complicated ADA recognition process for DSME centers

(Paul et al., 2018).

1.2.3 Diabetes-related Emergency Department (ED) Visits

Emergency department plays a vital role in the interface between the population and the healthcare system. Investigating patterns in Emergency Department (ED) visits can help identify patterns of health resource utilization, identify disease trends and emerging threats, and assess the magnitude and management of disease problems (Kellermann et al., 2013). Emergency Department visits substantially contribute to the economic burden of diabetes and diabetes-related complications. In addition, diabetes is considered an Ambulatory Care Sensitive Condition (ACSC), a condition in which appropriate ambulatory/outpatient care can prevent complications and the need for ED visits and hospitalization (Agency for Healthcare Research and Quality, 2001). Therefore, disparities in diabetes-related ED visits may reflect disparities in outpatient care access, continuity, and quality (Johnson et al., 2012).

1.2.3.1 Burden of Diabetes-related ED visits

The burden of emergency conditions and emergency department utilization vary worldwide. A systematic review by Chang et al. reported that low-income countries (LIC) had consistently lower ED visits, despite higher disease burdens (Birtwhistle et al., 2017). High-income countries (HIC), on the other hand, had substantial variations in ED utilizations but a lower burden of emergency conditions. However, the majority of ED visits in HIC result from non-communicable diseases, including diabetes and stroke. Approximately 13% of the 130 million ED visits in the US in 2018 were due to diabetes and diabetes-related complications (Centers for Disease Control and Prevention, 2021c, 2021d). In 2015, about 24% of all ED visits of patients aged 45 years or older were made by those with diabetes (Hall et al., 2018; Washington et al., 2006). There is evidence that the risk of ED visits is higher among persons with diabetes (68 visits/100 adults with diabetes) than the national average (40 visits/100 adults) (Centers for Disease Control and Prevention, 2021c, 2021d). According to the report of the National Health Interview Survey, 30% of people with diabetes had at least one ED visit in the past 12 months, which was higher than that of the general population (20%) in 2011 (McEwen & Herman, 2018).

1.2.3.2 Geographic Disparities and Temporal Trends of Diabetes-Related ED Visits

Southern United States has the highest age-adjusted diabetes-related ED visit risk (49.3 visits/1000 adults), while the western region has the lowest risk (34.6 visits/1000 adults) in 2016 (Uppal et al., 2022). The observed unequal distribution of diabetes-related ED visit risks could be due to the presence of wide-ranging disparities in diabetes prevalence (Barker et al., 2011), quality of diabetes care and outcomes (Johnson et al., 2012), access to primary and outpatient care, DSME program availability (Rutledge et al., 2017), and disproportionate burden of diabetes-related complications among populations with different sociodemographic characteristics (Benoit et al., 2020; Ginde et al., 2008; Menchine et al., 2012; Washington et al., 2006).

Overall, diabetes-related ED visit risks increased from 2007 to 2017. Populations in rural areas of the US had a consistently higher risk of ED visits than their counterparts in urban areas (Uppal et al., 2022). However, increasing trends observed in rural areas were not uniform across states. Patients in rural areas of New York, Kentucky, and Utah experienced an upward trend in ED visit risks from 2008 to 2014, while a downward trend was observed among rural patients in Florida, North Carolina, and Maryland during the same period. This suggests that national trends may not accurately reflect the burden of ED visits at the state level and emphasize the necessity of investigating ED visit risks at a lower geographic level, such as county or zip code (Uppal et al., 2022).

1.2.3.3 Predictors of Diabetes-related ED Visits

High ED utilization, for any reason, has been observed among traditionally underserved groups, such as Black, Hispanic, uninsured, and low-income patients (Hong et al., 2007; B. C. Sun et al., 2003). Similar factors were responsible for high diabetes-related ED visits. Individuals of Black race, Hispanic ethnicity, older ages, and those without health insurance were reported to have significantly higher risks of diabetes-related ED visits in the US

(Menchine et al., 2012; Uppal et al., 2022). Similarly, a study conducted in Ontario, Canada, reported that individuals with high HbA1c had a significantly greater risk of diabetes-related ED visits and hospitalizations (Birtwhistle et al., 2017). These individuals tended to be male, younger, have low income, have multiple comorbidities, and live in rural or suburban areas (Birtwhistle et al., 2017).

Persons with diabetes who are either <20 years of age or >65 years old tend to have more ED visits compared to their counterparts in middle age (20-65 years). This is because younger persons tend to have type 1 diabetes, while older adults are more likely to have type 2 diabetes (Mayo Clinic, 2023). Previous studies reported that populations with type 1 diabetes were more likely to have recurrent ED visits due to hyperglycemia compared to those with type 2 diabetes (Yan et al., 2017). Additionally, patients with type 1 diabetes are completely dependent on insulin, while type 2 diabetes can be managed by oral hypoglycemic medications. Evidence suggests that medication-dependent patients manage diabetes better than insulin-dependent patients (Home et al., 2014; Vaughan et al., 2017). Furthermore, younger patients are generally less compliant or less experienced in managing diabetes than older patients in the case of both types of diabetes (Yan et al., 2017). However, older individuals (>65 years) with diabetes typically have multiple comorbidities and less capacity for blood glucose control, which contribute to increased risks for ED visits among these populations.

It has been reported that diabetes-specific ED use among non-Hispanic Black patients is approximately three times higher than among non-Hispanic White patients (Uppal et al., 2022). This might be due to the fact that non-Hispanic Black patients have higher risks of diabetes-related complications such as albuminuria, retinopathy, lower extremity amputation, end-stage renal disease (ESRD), and worse glycemic control than their non-Hispanic White counterparts (Canedo et al., 2018; Osborn et al., 2013). Several individual-level, environmental, and healthcare system-related factors are responsible for the higher burden of diabetes and diabetes-related complications among minority populations (Taylor et al., 2019). Obesity, low physical activity, poor self-management of blood glucose, and depression are some individual-level factors related to poor glycemic control among these populations (Spanakis & Golden, 2013). Environmental factors include living conditions that can impact nutrition, access to exercise, and exposure to toxins (LaVeist et al., 2009). Additionally, healthcare-related factors, such as poor healthcare access, low quality of healthcare, and lack of health insurance, are responsible for higher risks of diabetes-related complications (Hong et al., 2007; Kim et al., 2012). Disparities of diabetes-related ED use among minority populations could also be due to differences in healthcare-seeking behaviors, mistrust of the healthcare system, and overall low socioeconomic conditions (Arnett et al., 2016). Non-Hispanic Black people have higher risks of diabetes-related ED visits even after adjusting for insurance status, income, access to care, and glycemic control, probably due to poor health-seeking behaviors (Arnett et al., 2016; Heidemann et al., 2016). However, minority populations such as non-Hispanic Black or Hispanic are less likely to receive recommended diabetes preventive care (Taylor et al., 2019) and have low participation in DSME programs (Khan et al., 2021).

Rurality has been identified as a strong risk factor for ED visits due to any disease in the US (Greenwood-Ericksen & Kocher, 2019). Rural populations typically have a higher burden of chronic diseases and health risk factors, such as obesity, smoking, and opioid overuse but have limited access to primary care and health insurance. People without healthcare insurance coverage have higher diabetes-related ED visit risks than the insured population because they do not have primary or outpatient care access and, therefore, tend to suffer from diabetes-related complications (Agency for Healthcare Research and Quality, 2001). However, ED visits also vary among populations with different types of health insurance coverage. Expanding government insurance policies such as Medicaid and Medicare increased healthcare coverage and promoted healthcare-seeking behaviors among low-income individuals in both rural and urban settings. These individuals are likely to visit ED more frequently than privately insured individuals (Greenwood-Ericksen & Kocher, 2019; Uppal et al., 2022).

CHAPTER 2

Geographic Disparities and Temporal Changes of Diabetes Prevalence and Diabetes Self-Management Education Program Participation in Florida

Geographic disparities and temporal changes of diabetes prevalence and diabetes self-management education program participation in Florida

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A version of this chapter has been published in PloS One.

Citation:

Khan MM, Roberson S, Reid K, Jordan M, Odoi A. Geographic disparities and temporal changes of diabetes prevalence and diabetes self-management education program participation in Florida. PLoS One. 2021;16:e0254579. doi:10.1371/journal.pone.0254579.

My contribution to this chapter included conceptualization of the research idea, data analysis, as well as writing and revision of the manuscript.

2.1 Abstract

Although Diabetes Self-Management Education (DSME) programs are recommended to help reduce the burden of diabetes and diabetes-related complications, Florida is one of the states with the lowest DSME participation rates. Moreover, there is evidence of geographic disparities of not only DSME participation rates but the burden of diabetes as well. Understanding these disparities is critical for guiding control programs geared at improving participation rates and diabetes outcomes. Therefore, the objectives of this study were to: (a) investigate geographic disparities of diabetes prevalence and DSME participation rates; and (b) identify predictors of the observed disparities in DSME participation rates.

Behavioral Risk Factor Surveillance System (BRFSS) data for 2007 and 2010 were obtained from the Florida Department of Health. Age-adjusted diabetes prevalence and DSME participation rates were computed at the county level and their geographic distributions visualized using choropleth maps. Significant changes in diabetes prevalence and DSME participation rates between 2007 and 2010 were assessed and counties showing significant changes were mapped. Clusters of high diabetes prevalence before and after adjusting for common risk factors and DSME participation rates were identified, using Tango's flexible spatial scan statistics, and their geographic distribution displayed in maps. Determinants of the geographic distribution of DSME participation rates and

predictors of the identified high rate clusters were identified using ordinary least squares and logistic regression models, respectively.

County level age-adjusted diabetes prevalence varied from 4.7% to 17.8% while DSME participation rates varied from 26.6% to 81.2%. There were significant ($p \leq 0.05$) increases in both overall age-adjusted diabetes prevalence and DSME participation rates from 2007 to 2010 with diabetes prevalence increasing from 7.7% in 2007 to 8.6% in 2010 while DSME participation rates increased from 51.4% in 2007 to 55.1% in 2010. Generally, DSME participation rates decreased in rural areas while they increased in urban areas. High prevalence clusters of diabetes (both adjusted and unadjusted) were identified in northern and central Florida, while clusters of high DSME participation rates were identified in central Florida. Rural counties and those with high proportion of Hispanics tended to have low DSME participation rates.

The findings confirm that geographic disparities in both diabetes prevalence and DSME participation rates exist. Specific attention is required to address these disparities especially in areas that have high diabetes prevalence but low DSME participation rates. Study findings are useful for guiding resource allocation geared at reducing disparities and improving diabetes outcomes.

2.2 Introduction

Diabetes is the seventh leading cause of death in the United States (US) and is characterized by Fasting Plasma Glucose (FPG) levels of ≥126 mg/dl while the FPG levels for prediabetes is 100-<126 mg/dl (American Diabetes Association, 2020). Over the last 20 years, the number of diabetic patients in the US has doubled and is projected to double or triple again by 2050 (Centers for Disease Control and Prevention, 2010). The economic burden of the condition is quite significant as evidenced by the fact that the average healthcare expenditure of a diabetic patient is 2.3 times higher than that of a non-diabetic. The total estimated cost of the condition in the US, including direct (treatment) and indirect (reduced productivity) costs, is $327 billion (Yang et al., 2018). The increasing burden of diabetes observed in the US has been reported in Florida as well. For example, the prevalence of diabetes among Florida adults increased from 5.2% in 1995 to 12.6% in 2018 (Florida Department of Health, 2017, 2019a). Moreover, almost 7.3% of adults in Florida have prediabetes (Okwechime et al., 2015). Individuals with prediabetes have a higher risk of developing diabetes compared to those that do not have the condition (Centers for Disease Control and Prevention, 2020c). On average, Florida spends $24.3 billion each year on diabetes and prediabetes (American Diabetes Association, 2016; Florida Department of Health, 2017).

The National Diabetes Educational Program (NDEP) was jointly launched by the Department of Health and Human Services (HHS), National Institutes of Health (NIH), and Centers for Disease Control and Prevention (CDC) to provide educational and preventive programs intended to reduce the risks and complications of diabetes (Siminerio et al., 2018). The Diabetes Self-management Education (DSME) is one of those educational programs developed to minimize development of diabetes related complications and improve clinical outcomes as well as quality of life of diabetic patients (Centers for Disease Control and Prevention, 2018b; Powers et al., 2016). Unfortunately, less than 7% of newly diagnosed diabetic patients in the US participate in this program within the first year of diagnosis (Li et al., 2014). Moreover, only about 54.4% of diabetics in the US attended DSME classes in 2015. This was the lowest participation rate among all the existing CDC recommended preventive measures for diabetes. In Florida, the rate was even lower (45.2%) than the national average (Centers for Disease Control and Prevention, 2017b).

There is evidence of geographic and sociodemographic disparities related to diabetes prevalence (Lord et al., 2020), DSME program availability (Rutledge et al., 2017), emergency department visits (Ginde et al., 2008), and hospitalizations in the US (Fayfman et al., 2016). However, disparity in DSME participation has not been investigated. Identifying these disparities is important for guiding health planning and service provision to minimize/eliminate the disparities, reduce the burden of diabetes and diabetes related complications and improve population health. Therefore, the objectives of this study were to: (a) investigate geographic disparities and temporal changes in diabetes prevalence and DSME program participation rates in Florida between 2007 and 2010; (b) identify predictors of the geographic disparities in DSME participation rates in Florida. Study findings will be useful for guiding prevention and control programs and policy.

2.3 Materials & Methods

2.3.1 Study Area

This retrospective ecological study was performed in the state of Florida and included data from the years 2007 and 2010. Florida has 67 counties many of which are located in the diabetes belt which is an area of the US having a higher prevalence of diabetes (11.7%) than the rest of the country (8.5%) (Barker et al., 2011). As of 2018, Florida was the most populous state in the southeastern US with approximately 20.9 million people. It has the second-highest number of the elderly (≥65 years old) population in the US (Florida Department of Health, 2020c; Kilduff, 2021). The age distribution of the population is 22.3% 0-19 years old, 19.2% 20-34 years old, 12.0% 35-44 years old, 13.2% 45-54 years old, 13.3% 55-64 years old and 20% ≥65 years old. Approximately 51% of the population is female. The majority (77.4%) of the population are white, 16.9% are black while all other races comprise 5.7% of the population. By ethnicity, 25.7% of the population is Hispanic-Latino while the rest are non-Hispanic (Florida

Department of Health, 2020c). The state has both urban and rural areas with Miami-Dade being the most urban and populous county (2,804,160 residents) and Lafayette county being the most rural and least populous (8,367 residents) (Figure 2.1) (Florida Department of Health, 2020c).

2.3.2 Data Sources

Data on diabetes and DSME, for the years 2007 and 2010, were extracted from the Behavioral Risk Factor Surveillance System (BRFSS) datasets that were obtained from the Florida Department of Health. The 2007 and 2010 are the latest available DSME participation data currently available because the Florida 2016 and 2019 BRFSS questionnaire did not include questions on DSME participation. The BRFSS collects data from adults 18 years of age or older. Diabetes status was determined based on the respondent’s report of having been told by a doctor that they had diabetes not related to pregnancy. The survey did not make a distinction between type 1 and 2 diabetes. The DSME participation was determined using diabetic patients’ responses to the question regarding if they had ever participated in a DSME program. Additional data extracted from the BRFSS datasets included respondent’s county of residence, age, gender, race, marital status, educational attainment, healthcare accessibility, body mass index (BMI), exercise, smoking, and drinking habits. Rural counties were identified based on the classification available at the Florida Department of Health website (Florida Department of Health, 2020c). This

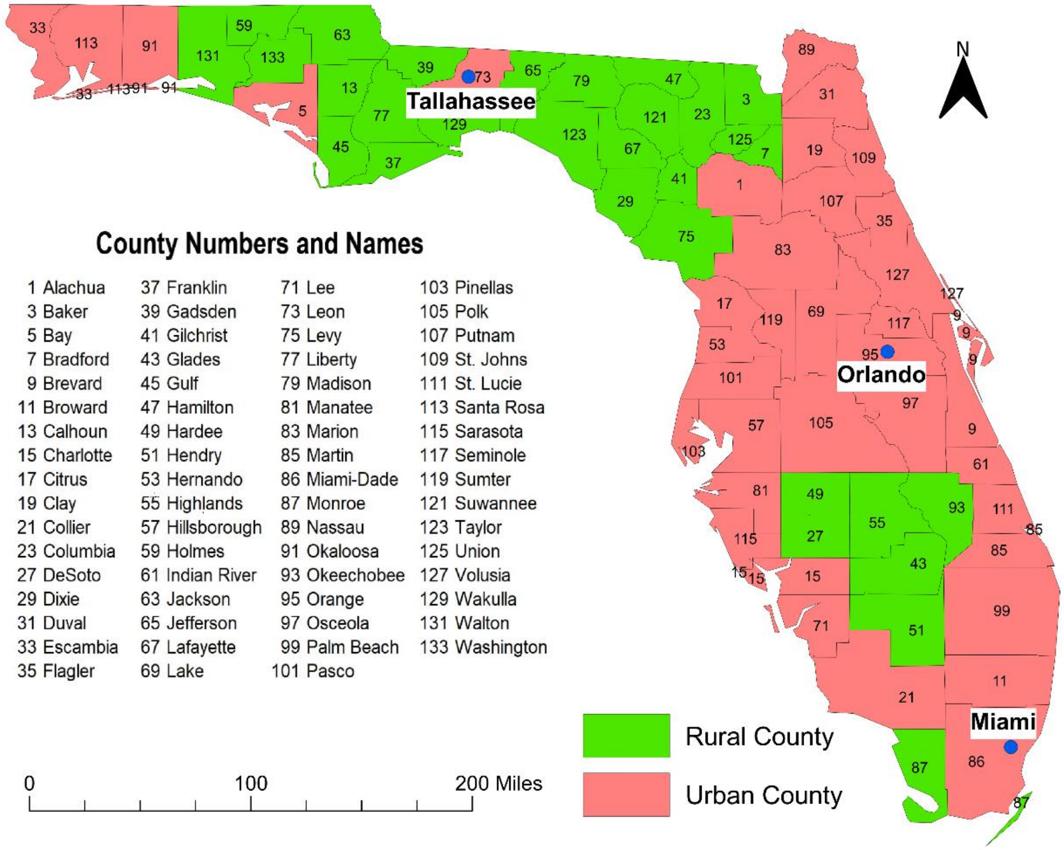

Figure 2.1: Map of Florida showing geographic distribution of urban and rural counties. Figure was created using the Free and Open Source Geographic Information System (GIS) software, QGIS.

classification is based on the population density of the county. Thus, rural counties were defined as those with population density of ≤100 persons per square mile. County-level proportion of the rural population, unemployed population, and median income were obtained from the County Health Rankings and Roadmap (CHRR) website (Robert Wood Johnson Foundation and The University of Wisconsin Population Health Institute, 2020). County-level proportion of population below the federal poverty level was obtained from the American Community Survey (ACS) 5-years estimates (US Census Bureau, 2020). Cartographic boundary file for county-level geographic analyses was downloaded from the United States Census Bureau TIGER Geodatabase (United States Census Bureau, 2021).

2.3.3 Data Preparation and Visualization

The BRFSS data were aggregated to the county level using SAS 9.4 (SAS Institute inc., 2017). Since these data were collected using a complex survey design, a weight variable (created by the US Centers for Disease Control and Prevention [CDC]) was used for all individual level analyses (Florida Department of Health, 2010, 2020a). Thus, all county-level estimates/variables, derived from individual level survey responses, were computed using the weight variable to ensure that the estimates were generalizable to all Florida adults. Therefore, computation of county-level percentages/frequencies involved using SURVEYFREQ procedure of SAS and specifying the strata variable (_STSTR), cluster variable (_PSU) as well as a sampling weight variable (_FINALWTSTAT). County level variables included in the study were: percentage of population in each of the following variable categories: DSME participation (Yes/No), BMI categories (<25 [Neither overweight nor obese], 25-30 [Overweight], and >30 [Obese]); Education (≤High school education, Some college education, College education); Participation in any physical activities (Yes/No); Ever smoked (Yes/No); Heavy alcohol consumption defined as adult men having more than two drinks per day and adult women having more than one drink per day (Yes/No); Race and ethnicity (non-Hispanic White, non-Hispanic Black, Hispanic, and Others); Gender (Male, Female); Health status (Good, Fair or poor); Used insulin for controlling diabetes (Yes/No); Had limited activity due to physical, mental or emotional problems (Yes/No); Had retinopathy as a complication of diabetes (Yes/No); Availability of primary health care provider (Yes/No); Marital status (Married, Divorced or widowed or separated, Never married); Age (Population of 18-44 years, >44-64 years, and ≥65 years); population ≥25 years with a college degree; population living below the federal poverty level. Direct age-standardized county-level diabetes prevalence was calculated using the 2000 population of Florida as the standard (Klein & Schoenborn, 2001). Since the BRFSS data only contains data from respondents aged ≥18 years, county-level age-adjusted diabetes prevalence were computed using the following age categories: 18-44, >44-64 and ≥64 years (Klein & Schoenborn, 2001).

2.3.4 Descriptive Analysis

All descriptive analyses were performed in SAS 9.4 (SAS Institute inc., 2017). Normality of continuous county-level variables were assessed using Q-Q plots and Shapiro-Wilk tests. The Shapiro-Wilks test was used because it has been shown to have high power compared to other common methods such as Kolmogorov-Smirnov and Anderson-Darling (Mohd Razali & Bee Wah, 2011). Mean and confidence intervals were used to summarize normally distributed variables while median and lower-upper quartiles were used for variables showing deviations from normality.

2.3.5 2007 to 2010 Comparisons

One-tailed tests of equality of proportions were performed to identify significant increases or decreases in diabetes prevalence and DSME participation rates between 2007 and 2010 using STATA (StataCorp., 2019) command ‘prtest’. Simes method was used to adjust for multiple comparisons (Simes, 1986).

2.3.6 Clusters of High Diabetes Prevalence and High DSME Participation Rates

A Poisson model, implemented in SAS 9.4, was used to adjust diabetes prevalence for the following known risk factors: age, gender, race/ethnicity, and BMI (Centers for Disease Control and Prevention, 2020b; National Institute of Diabetes and Digestive and Kidney diseases, 2016). Tango’s flexible spatial scan statistics (FSSS), implemented in FlexScan (Tango & Takahashi, 2005), was then used to identify circular and irregularly shaped spatial clusters of both unadjusted and adjusted high diabetes prevalence. Tango's FSSS was also used to identify clusters of high DSME participation rates. Poisson probability models with restricted log likelihood (LLR) ratio (specifying alpha of 0.2) and maximum cluster size of 15 counties were specified to preclude potential inclusion of counties with non-elevated prevalence proportions or participation rates. To identify statistically significant clusters, 999 Monte Carlo replications were used specifying a critical p-value of 0.05. For each outcome, the significant cluster with the largest value of restricted LLR was identified as the primary cluster. The rest of the significant clusters were secondary clusters and were ranked based on their restricted LLR values. Clusters with prevalence ratios (PR) or participation rate ratios (PRR) less than 1.2 were not reported to avoid reporting very low prevalence or low rate clusters.

2.3.7 Predictors of Geographic Distribution of DSME Participation Rates

To investigate the predictors of county-level DSME participation rates, a multivariable ordinary least squares regression model was built using SAS 9.4 (SAS Institute inc., 2017) in two steps. The outcome variable was specified as county-level DSME participation rates. The 1st step of model building involved univariable assessments to identify potential predictors of DSME participation rates. Variables considered for potential univariable association with participation rates are listed in Table 2.1. Only potential predictor variables significant at a liberal $p \leq 0.15$ were considered for building the multivariable model in the 2nd step. Spearman's rank correlation coefficient was used to identify highly correlated ($r \geq 0.7$) variables. Only one of a pair of highly correlated variables was retained for assessment in the multivariable model. The decision regarding which of a pair of highly correlated variables to retain was based on biological and statistical considerations. The 2nd step involved building a multivariable ordinary least squares regression model using a manual backwards elimination approach using a critical p-value of ≤ 0.05. Confounding was assessed using change in regression coefficients of variables in the model when it was run with and without a suspected confounder. If removal of a suspected confounding variable resulted in a change of 20% or more of any of the other variables in the model, then the variable was kept in the model as a confounder regardless of its statistical significance. Biologically meaningful two-way interaction terms of variables in the final main effects model were assessed with the aim of keeping significant ones. Multicollinearity was assessed using both variance inflation factor (VIF) and multicollinearity condition number. Values of VIF>10 or multicollinearity condition number >20 were considered indicative of multicollinearity. Heteroskedasticity and normality of residuals were assessed using White and Jarque-Bera tests, respectively. Robust Lagrange Multiplier (LM) tests, employing inverse distance spatial weights, were used to assess for spatial dependence of residuals.

Table 2.1: Summary statistics of variables considered as potential predictors of county-level Diabetes Self-management Education (DSME) program participation and its hotspots in Florida, 2010.

Predictor variable	Mean	SD[1]	Median	Minimum	Maximum	IQR[2]
Proportion of having normal and less than normal weight	0.333	0.061	0.336	0.180	0.460	0.071
Proportion of having overweight*	0.367	0.042	0.710	0.246	0.474	0.043
Proportion of being obese	0.300	0.069	0.293	0.173	0.497	0.079
Proportion of smokers*	0.507	0.067	0.519	0.333	0.664	0.102
Proportion of heavy drinkers	0.055	0.019	0.054	0.018	0.104	0.027
Proportion of doing exercise	0.734	0.054	0.736	0.599	0.856	0.071
Proportion of having overall good health*	0.795	0.057	0.797	0.633	0.889	0.070
Proportion of having overall poor health*	0.205	0.057	0.203	0.111	0.367	0.070
Proportion of having limited activity due to health problems*	0.264	0.046	0.261	0.184	0.454	0.061
Proportion of having high school or less education	0.438	0.122	0.439	0.200	0.679	0.201
Proportion of having some college education	0.282	0.045	0.282	0.176	0.403	0.056
Proportion of having college education*	0.280	0.108	0.266	0.118	0.519	0.175
Proportion of being white, non-Hispanic*	0.790	0.110	0.804	0.261	0.921	0.118
Proportion of being black, non-Hispanic*	0.083	0.071	0.061	0.018	0.445	0.079
Proportion of being other, non-Hispanic*	0.045	0.024	0.039	0.006	0.115	0.031
Proportion of being Hispanic*	0.082	0.077	0.068	0.006	0.537	0.069
Proportion of being married	0.632	0.053	0.638	0.509	0.760	0.077
Proportion of being divorced/widowed/separated*	0.222	0.038	0.221	0.130	0.372	0.046
Proportion of being never married	0.146	0.047	0.139	0.057	0.269	0.064
Proportion male*	0.518	0.052	0.489	0.468	0.708	0.062
Proportion female*	0.482	0.052	0.511	0.292	0.532	0.062
Proportion with age 18 to 44 years	0.381	0.087	0.386	0.183	0.575	0.125
Proportion with age 45 to 64 years*	0.394	0.075	0.382	0.288	0.555	0.132
Proportion with age equal or greater than 65 years*	0.224	0.069	0.204	0.102	0.397	0.093
Median household income (in $10,000)*	4.181	0.691	4.118	3.097	6.084	1.004
Proportion of being unemployed	0.110	0.019	0.114	0.082	0.156	0.027

Table 2.1 Continued

Predictor variable	Mean	SD[1]	Median	Minimum	Maximum	IQR[2]
Proportion of having diabetes	0.096	0.026	0.095	0.047	0.178	0.036
Proportion that take insulin	0.302	0.086	0.293	0.128	0.526	0.112
Proportion that have diabetic complications (retinopathy)*	0.201	0.065	0.188	0.094	0.467	0.073
Proportion that have regular healthcare provider access*	0.799	0.055	0.805	0.560	0.902	0.070
Proportion of rural population*	0.375	0.323	0.238	0.000	1.000	0.590
Proportion that have insurance coverage	0.741	0.079	0.753	0.482	0.911	0.116
Proportion with age ≥25 years with a college degree*	0.294	0.112	0.286	0.126	0.553	0.182
Proportion below the federal poverty level*	0.177	0.051	0.165	0.098	0.297	0.082

[1]Standard deviation
[2]Interquartile range
*Non-normally distributed variables

2.3.8 Predictors of Clusters of High DSME Participation Rates

To investigate the predictors of clusters of high DSME participation rates, logistic regression model was built in SAS 9.4 (SAS Institute inc., 2017). The outcome variable for the logistic regression was a binary variable (Yes/No) indicating whether or not a county belonged to a high DSME participation rate cluster. The logistic model was also built in two steps as described above except in this case the outcome variable was dichotomous (Yes/No) representing whether a county was part of a high DSME participation rate cluster or not. Goodness-of-fit of the logistic model and spatial dependence were assessed using Hosmer-Lemeshow test and Moran's I using inverse distance spatial weights, respectively (Hosmer et al., 1988; Moran, 1950).

2.3.9 Cartographic Displays

All cartographic displays were generated using the Free and Open Source Geographic Information System (GIS) software, QGIS (QGIS Development Team, 2021). The prevalence estimates of diabetes, DSME participation rates, and its predictors, as well as significant spatial clusters, were displayed on maps. Jenk's optimization classification scheme was used to determine critical intervals for choropleth maps. In addition, statistically significant changes in county-level estimation of diabetes prevalence and DSME participation rates between 2007 and 2010 were displayed using manual intervals classification scheme.

2.3.10 Ethics Approval

This study was reviewed by the University of Tennessee Institutional Review Board (Number: UTK IRB-20-05707-XM) and determined to be eligible for exempt review under 45 CFR 46.101. Category 4: Secondary research for which consent is not required. The study used anonymized secondary data provided to the investigators in such a manner that the identity of the human subjects cannot be ascertained directly or through identifiers linked to the subjects. The investigators did not contact the subjects and did not re-identify subjects.

2.4 Results

2.4.1 Spatial Distribution

The age-adjusted diabetes prevalence varied across counties in Florida ranging from 4.7% to 17.8% (Figure 2.2). In 2007, 16 counties in the panhandle, north-central and mid-Florida had diabetes prevalence greater than 10% while almost half (28) of the counties in those same areas had prevalence greater than 10% in 2010. Most of the counties with high prevalence were located in rural areas (Figures 2.1 and 2.2). On the other hand, diabetes prevalence of several urban counties in southern and northeast Florida were lower in 2010 compared to 2007.

Diabetes self-management Education program participation rates also varied across counties in Florida ranging from 26.6% to 81.2% (Figure 2.2). Between 2007 and 2010, DSME participation rates decreased in several counties of the

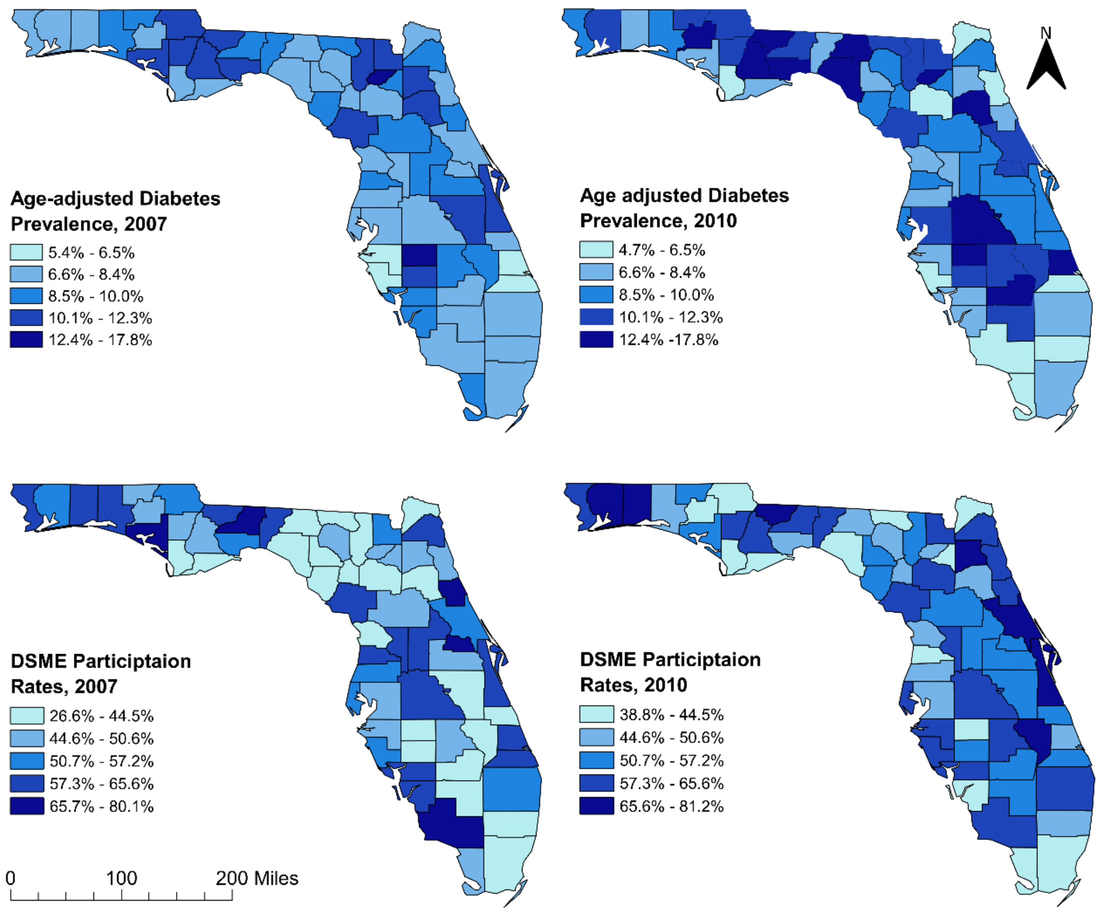

Figure 2.2: Age-adjusted county level diabetes prevalence and Diabetes Self-management Education Program participation rates in Florida, 2007-2010. Figure was created using the Free and Open Source Geographic Information System (GIS) software, QGIS.

central panhandle area of northern Florida while they increased in the entire north-central to mid-Florida. Overall, between 2007 and 2010, DSME participation rates decreased in rural areas while they increased in urban areas (Figures 2.1 and 2.2).

2.4.2 Changes in Diabetes Prevalence and DSME Participation Rates, 2007-2010

There was a statistically significant ($p<0.001$) increase in the overall state-wide age-adjusted diabetes prevalence from 7.7% in 2007 to 8.6% in 2010. Sixty-two of the 67 counties had significant changes (either increases or decreases) in diabetes prevalence (Figure 2.3). The five counties that did not have significant changes in diabetes prevalence over the time period were Calhoun, Franklin, Lafayette, Columbia, and Pasco counties (Figures 2.1 and 2.3). Statistically significant ($p<0.05$) decreases in diabetes prevalence were observed in 35.5% (22/62) of the counties that had significant changes, while significant ($p<0.05$) increases were seen in 64.5% (40/62) of these counties. The largest increase in diabetes prevalence (14.1%, a relative increase of 155.8%) was observed in St. Lucie (south-east coastal county) whereas the largest decrease (5.1%, a relative decrease of 36.1%) was observed in St. Johns (north-east coastal county) (Figures 2.1 and 2.3).

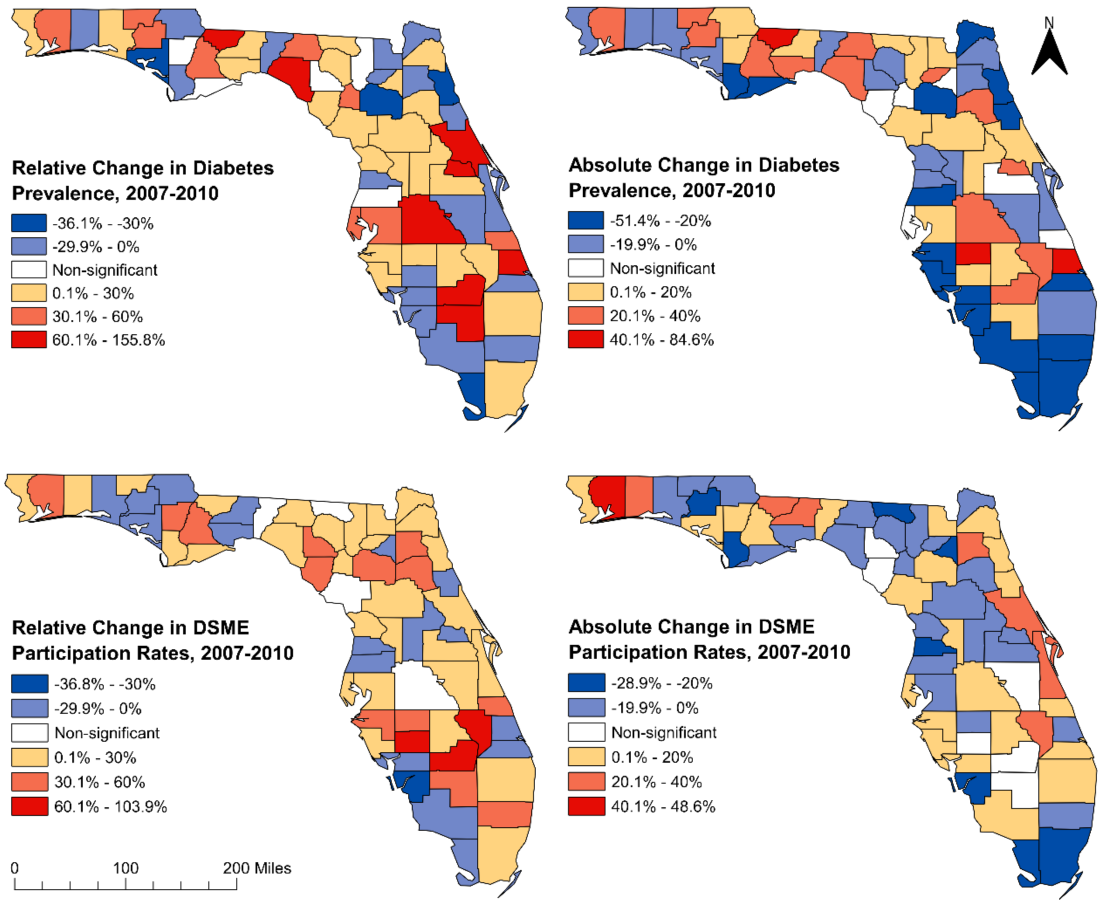

Figure 2.3: Relative and absolute changes of diabetes prevalence and Diabetes Self-management Education Program participation rates in Florida between 2007 and 2010. Figure was created using the Free and Open Source Geographic Information System (GIS) software, QGIS.

Significant (p<0.001) state-wide changes in DSME participation rates were also observed in almost all the counties with the exception of Jefferson, Hamilton, Levy, and Polk counties (Figures 2.1 and 2.3). Overall, there was a statistically significant (p<0.001) increase in DSME participation rates from 51.4% in 2007 to 55.1% in 2010. Lee county had the largest significant decrease (39.6%, a relative decrease of 36.8%), while Glades county had the largest increase (54.3%, a relative increase of 103.9%). Of the counties that had significant changes in DSME participation rates, 28.6% (18/63) had significant decreases while 71.4% (45/63) had increases. It is worth noting that seven counties (Walton, Washington, Leon, Wakulla, Lake, Seminole, and St. Lucie) had significant increases in diabetes prevalence, but significant decreases in DSME participation (Figures 2.1 and 2.3). It was concerning to note that although St. Lucie had the largest increase (155.8%) in diabetes prevalence, it had 20.9% decrease in DSME participation rate. Moreover, a similar pattern was also observed in Leon county where the state administrative capital is located (Figures 2.1 and 2.3).

2.4.3 Clusters of Diabetes Prevalence and DSME Participation Rates

2.4.3.1 Unadjusted Diabetes Prevalence Clusters

Consistent with the increase in diabetes prevalence observed in northern and mid-Florida rural counties (Figure 2.3), significant high-prevalence diabetes spatial clusters were identified in these areas (Table 2.2 and Figure 2.4). There were increases in both the numbers of counties involved in the clusters and sizes of the population affected between 2007 and 2010 (Table 2.2 and Figure 2.4). A total of 4 and 5 significant spatial high-prevalence diabetes clusters were detected in 2007 and 2010, respectively. In 2007, three similar sized clusters (each containing 6 counties) of high diabetes prevalence were detected in northern and central Florida (Table 2.2 and Figure 2.4). The primary cluster in 2007 included only urban counties of central Florida while a secondary cluster included rural counties of central panhandle excluding Leon County, where the state capital is located. It is worth mentioning that this secondary cluster had the highest prevalence ratio (PR=1.45: p=0.001) in 2007. Another secondary cluster (Secondary Cluster 1) that was identified in 2007 had 23% higher diabetes prevalence than the state average and included several counties (Hamilton, Columbia, Union, Baker, Clay, Duval), at the urban-rural interface in the north, that were not part of any cluster in 2010 (Figures 2.1 and 2.4). Interestingly, only two of the counties (Lake and Osceola) that were part of the primary cluster in 2007 were also part of a cluster (Primary Cluster) in 2010. The primary cluster in 2010 was much larger (included 13 counties) and was located in mid-Florida (Table 2.2 and Figure 2.4). Moreover, the northern secondary cluster identified in 2007 expanded in 2010 and included Leon county, an urban county where the state capital is located. In 2010, the cluster that had the highest diabetes prevalence ratio (PR=1.46; p=0.001) included two rural counties of north Florida,

Table 2.2: Purely spatial unadjusted diabetes prevalence clusters in Florida, 2007 and 2010.

Cluster	Population	Observed cases	Counties included[2]	No of Counties included	PR[1]	*p*-value
			2007			
Primary	1,239,259	123,826	9, 35, 69, 83, 97, 107	6	1.29	0.001
Secondary 1	857,484	82,033	3, 19, 23, 31, 47, 125	6	1.23	0.001
Secondary 2	243,828	27,400	5, 13, 39, 63, 77, 129	6	1.45	0.001
Secondary 3	126,678	11,846	53	1	1.21	0.001
			2010			
Primary	3,900,382	427,501	27, 49, 55, 57, 61, 69, 93, 95, 97, 105, 111, 117, 127	13	1.26	0.001
Secondary 1	374,678	44,435	13, 39, 59, 63, 73, 77, 129, 133	8	1.36	0.001
Secondary 2	116,875	13,885	113	1	1.37	0.001
Secondary 3	33,972	4,320	79, 123	2	1.46	0.001
Secondary 4	38,710	4,464	43, 51	2	1.33	0.001

[1]Prevalence ratio

[2][3= Baker 5= Bay 9= Brevard 13= Calhoun 19= Clay 23= Columbia 27= Desoto 31= Duval 35= Flagler 39= Gadsden 43= Glades 47= Hamilton 49= Hardee 51= Hendry 53= Hernando 55= Highlands 57= Hillsborough 59= Holmes 61= Indian River 63= Jackson 69= Lake 73= Leon 77= Liberty 79= Madison 83= Marion 93= Okeechobee 95= Orange 97= Osceola 105= Polk 107= Putnam 111= St. Lucie 113= Santa Rosa 117= Seminole 123= Taylor 125= Union 127= Volusia 129= Wakulla]

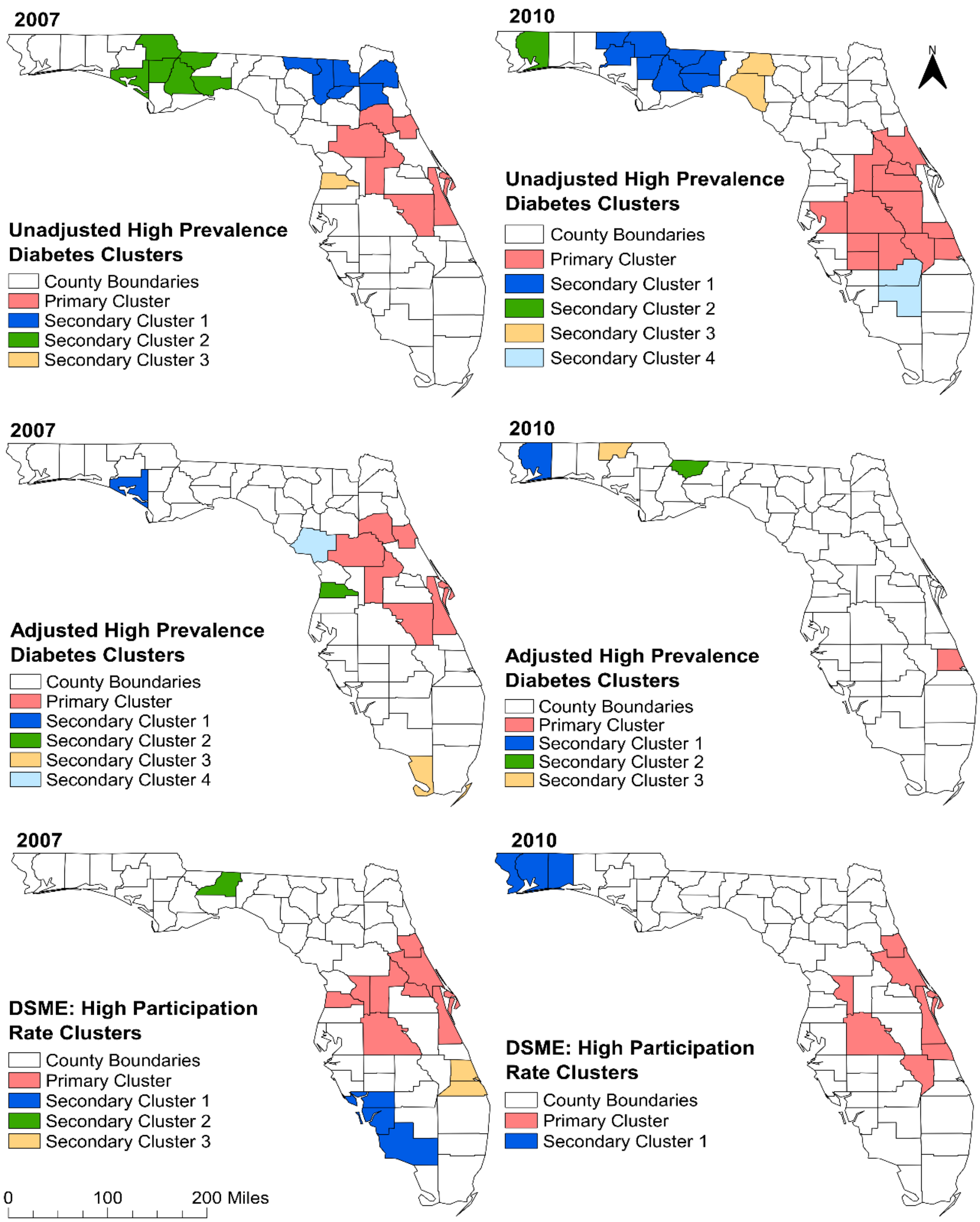

Figure 2.4: Clusters of high diabetes prevalence and high Diabetes Self-management Education Program participation rates identified in Florida using Tango's flexible spatial scan statistics, 2007 and 2010. Figure was created using the Free and Open Source Geographic Information System (GIS) software, QGIS.

Madison and Taylor counties (Figures 2.1 and 2.4). Both counties were not even a part of any cluster in 2007.

Some high-prevalence clusters were persistent over the study period. These included counties in northern Florida (Jackson, Calhoun, Gadsden, Liberty, Wakulla counties) and mid-Florida (Lake, Osceola counties) (Figures 2.1 and 2.4). All of them were rural counties, except Lake and Osceola. Some counties transitioned from non-clusters to statistically significant high-prevalence clusters and these were mostly located in mid-Florida. However, clusters located in north-central Florida had the opposite trend of transitioning from significant clusters to non-clusters counties. Ten counties (both urban and rural) were clusters in 2007 but became non-clusters in 2010. With the exception of Indian River, St Luis and Volusia counties, the majority of the urban counties (from both east and west coasts) and spanning from north to south, transitioned to or remained as non-cluster counties in 2010 (Figures 2.1 and 2.4). Brevard county that was part of the primary cluster in 2007 was not part of a cluster in 2010 (Table 2.2; Figures 2.1 and 2.4).

2.4.3.2 Risk-Factor Adjusted Diabetes Prevalence Clusters

The number of counties that were part of high prevalence clusters in both 2007 and 2010 were lower for adjusted than unadjusted prevalence clusters (Tables

2.2 and 2.3; Figure 2.4). Several of the northern counties (in both 2007 and 2010) that were part of the unadjusted prevalence clusters were not in clusters after risk-factor adjustment (Figure 2.4). In a nutshell, although significant clusters were still identified after risk adjustment, the number of affected counties significantly reduced after risk adjustment implying that the risk factors explained the high prevalence in several counties that were part of the unadjusted clusters.

2.4.3.3 DSME Participation Rates Clusters

The spatial distribution of High DSME participation rate clusters (Figure 2.4) are consistent with the distribution of the rates in both 2007 and 2010 (Figure 2.2). There were 4 and 2 high participation rate spatial clusters of DSME participation rates in 2007 and 2010, respectively. The geographic sizes of the clusters identified in 2007 varied from one county (Secondary Cluster 2) to eight counties (Primary Cluster) (Table 2.2 and Figure 2.4). These clusters were mainly located in the South-west, mid and mid-east part of Florida (Figure 2.4). The primary cluster was the largest in both geographic size (included 8 counties) and size of population in the cluster (2.1 million) and was located in mid-Florida. This cluster had a DSME participation rate 22% higher than the state average (Table 2.4). The single county cluster (Secondary Cluster2) was composed of Leon county, which is an urban county that houses the state capital (Figures 2.1 and 2.4). This cluster had the highest DSME participation rate ratio (PRR=1.56: p=0.001) implying that this county had 56% higher participation rate than the state

Table 2.3: Purely spatial risk-factor adjusted diabetes prevalence clusters in Florida, 2007 and 2010.

Cluster	Population	Observed cases	Counties included[2]	No of Counties included	PR[1]	*p*-value
			2007			
Primary	1,239,259	123,822	9, 35, 69, 83, 97, 107	6	1.26	0.001
Secondary 1	127,334	9,992	5	1	1.5	0.001
Secondary 2	126,678	11,845	53	1	1.23	0.001
Secondary 3	65,436	5,874	87	1	1.28	0.001
Secondary 4	28,812	2,970	75	1	1.23	0.001
			2010			
Primary	218,337	30,829	111	1	1.44	0.001
Secondary 1	116,875	13,884	113	1	1.33	0.001
Secondary 2	38,127	6,790	39	1	1.39	0.001
Secondary 3	15,549	1,904	59	1	1.3	0.001

[1]Prevalence ratio

[2][5= Bay 9= Brevard 35= Flagler 39= Gadsden 53= Hernando 59= Holmes 69= Lake 75= Levy 83= Marion 87= Monroe 97= Osceola 107= Putnam 111= St. Lucie 113= Santa Rosa]

Table 2.4: Purely spatial clusters of High Diabetes Self-Management Education (DSME) Program Participation Rates in Florida, 2007 and 2010.

Cluster	Population	Observed cases	Counties included in cluster[2]	No. of Counties included	PRR[1]	*p-value*
			2007			
Primary	2,052,527	128,477	9, 35, 53, 69, 105, 117, 119, 127	8	1.22	0.001
Secondary 1	854,415	57,913	15, 21, 71	3	1.29	0.001
Secondary 2	207,233	12,676	73	1	1.56	0.001
Secondary 3	311,922	13,961	85, 111	2	1.21	0.001
			2010			
Primary	1,606,390	138,762	9, 35, 61, 93, 105, 119, 127	7	1.21	0.001
Secondary 1	500,273	38,086	33, 91, 113	3	1.29	0.001

[1]Participation Rate Ratio

[2][9= Brevard 15= Charlotte 21= Collier 33= Escambia 35= Flagler 53= Hernando 61= Indian River 69= Lake 73= Leon 85= Martin 91= Okaloosa 93= Okeechobee 105= Polk 111= St. Lucie 113= Santa Rosa 117= Seminole 119= Sumter 127= Volusia]

average. Although DSME participation rates increased from 2007 to 2010, fewer clusters were found in the western part of the panhandle and mid-east coast of Florida in 2010. However, DSME participation rate of the primary cluster in 2010 was almost equal (21% higher than the state average) to the rate of the primary cluster of 2007.

Five Counties in mid-Florida (Sumter, Polk, Brevard, Volusia and Flagler) were consistently in high DSME participation rate clusters in 2007 and 2010 (Figures 2.1 and 2.4). Despite being a non-significant diabetes cluster county in 2007 and 2010, Sumter county was consistently part of a primary high DSME participation rate cluster in both 2007 and 2010 (Figures 2.1 and 2.4). Leon and several other counties of south-west Florida, which were significant clusters in 2007, became non-significant in 2010 (Figures 2.1 and 2.4).

2.4.3.4 Overlaps of Diabetes Prevalence and DSME Participation Rate Clusters

The geographical locations of the clusters of diabetes prevalence (both adjusted and unadjusted) rarely overlapped with those of DSME participation rates. However, three significant cluster counties of diabetes prevalence in 2007 (Hernando, Lake, and Flagler) were also significant high DSME participation rate cluster in 2007 (Figures 2.1 and 2.4). Similar overlaps were observed in Volusia, Polk, and Indian River counties in 2010 (Figures 2.1 and 2.4). While Leon county transitioned from not being part of a cluster (in 2007) to belonging to a high diabetes prevalence primary cluster (in 2010), the exact opposite happened in case of DSME participation rate since it transitioned from being part of a high DSME participation rate cluster (in 2007) to not being part of a cluster (in 2010).

2.4.4 Predictors of Disparities in DSME Participation Rates

Table 2.5 shows the univariable (unadjusted) associations of each of the predictors with DSME participation rate. Based on the multivariable model, significant predictors of DSME participation rates were proportion of rural population and proportion of Hispanic population (Table 2.6). There was also significant effect modification between the two variables. Thus, the relationship between the proportion of rural population and DSME participation rate depends on the proportion of Hispanic population and vice versa. There was no evidence of non-normality ($p=0.84$) or heteroskedasticity ($p=0.49$) of residuals of the OLS model. Additionally, both the robust Lagrange multiplier tests for lag ($p=0.22$) and error ($p=0.33$) showed no evidence of spatial dependence of the OLS residuals. There was also no evidence of multicollinearity as evidenced by the fact that all VIF values were less than 10 (Table 2.6) and the multicollinearity condition number (6.15) was less than 20.

Table 2.5: Univariable associations between county characteristics and Diabetes Self-management Education (DSME) program participations in Florida, 2010.

Predictors	Diabetes Self-management Education (DSME) Participations	
	Coefficient (95% CI[1])	*p*-value[2]
Proportion of having normal and less than normal weight	-0.033 (-0.405, 0.339)	0.86
Proportion of having overweight	0.308 (-0.221, 0.836)	0.25
Proportion of being obese	-0.092 (-0.421, 0.237)	0.58
Proportion of smokers	-0.229 (-0.562, 0.105)	0.18
Proportion of heavy drinkers	0.071 (-1.118, 1.259)	0.91
Proportion of doing exercise	0.219 (-0.197, 0.635)	0.30
Proportion of having overall good health	0.344 (-0.046, 0.734)	0.08
Proportion of having overall poor health	-0.344 (-0.734, 0.046)	0.08
Proportion of having limited walking capacity	-0.281 (-0.766, 0.204)	0.25
Proportion of having high school or less education	-0.239 (-0.415, -0.063)	0.01
Proportion of having some college education	0.267 (-0.236, 0.770)	0.29
Proportion of having college education	0.263 (0.063, 0.463)	0.01
Proportion of being white, non-Hispanic	0.037 (-0.169, 0.242)	0.72
Proportion of being black, non-Hispanic	0.099 (-0.216, 0.416)	0.53
Proportion of being other, non-Hispanic	0.595 (-0.340, 1.530)	0.21
Proportion of being Hispanic	-0.222 (-0.512, 0.069)	0.13
Proportion of being married	0.405 (-0.007, 0.817)	0.05
Proportion of being divorced/widowed/separated	-0.342 (-0.934, 0.250)	0.25
Proportion of being never married	-0.300 (-0.776, 0.176)	0.21
Proportion male	-0.527 (-0.938, -0.116)	0.01
Proportion female	0.527 (0.116, 0.938)	0.01
Proportion with age 18 to 44 years	-0.074 (-0.333, 0.186)	0.57
Proportion with age 45 to 64 years	0.066 (-0.235, 0.367)	0.66
Proportion with age equal or greater than 65 years	0.039 (-0.289, 0.367)	0.81
Median household income (in $10,000)	0.038 (0.007, 0.070)	0.02
Proportion of being unemployed	-0.168 (-1.344, 1.007)	0.78
Proportion of having diabetes	0.228 (-0.625, 1.081)	0.60
Proportion that take insulin	-0.030 (-0.294, 0.234)	0.82
Proportion that have diabetic complications (retinopathy)	-0.182 (-0.527, 0.163)	0.30
Proportion that have regular healthcare provider access	0.477 (0.083, 0.871)	0.02
Proportion of rural population	-0.086 (-0.153, -0.019)	0.01
Proportion that have insurance coverage	0.378 (0.108, 0.648)	0.01
Proportion with age ≥25 years with a college degree*	0.250 (0.058, 0.442)	0.01
Proportion below the federal poverty level*	-0.269 (-0.711, 0.173)	0.23

[1]Confidence interval
[2]Potential statistical significance was assessed using a liberal critical p=0.15

Table 2.6: Results of ordinary least square regression model showing predictors of Diabetes Self-management Education (DSME) participation rates at the county level in Florida, 2010.

Predictor Variable	Coefficient (95% CI[1])	SE[2]	t-value	p-value[3]	VIF[4]
Proportion of being Hispanic	-0.586 (-0.914, -0.259)	0.164	-3.58	0.0007	1.58
Proportion of rural population	-0.192 (-0.285, -0.010)	0.046	-4.15	0.0001	2.24
Proportion of Hispanic X Proportion of rural population Interaction	1.298 (0.191, 2.405)	0.554	2.34	0.02	2.12

[1]Confidence interval
[2]Standard error
[3]Statistical significance was assessed using a critical p=0.05
[4]Variance Inflation Factor

2.4.5 Predictors of Clusters of High DSME Participation Rates

Table 2.7 shows variables that were considered as potential predictors of clusters of high DSME participation rates. In the final model, only the proportion of rural residents had significant association with clusters of DSME participation rate (Table 2.8). The geographic distribution of the significant predictors of participation rates and clusters are shown in Figure 2.5. The proportion of Hispanic population showed a North-South gradient with the lowest proportions being observed in the north and highest in the South. In contrast, the proportion of rural population showed the reverse spatial trend with the lowest proportions of rural residents being observed in the South and highest in the north (Figure 2.5). Hosmer-Lemeshow goodness-of-fit test indicated no evidence of lack of fit ($p=0.58$). Finally, the Moran's I statistic showed no evidence of spatial dependence of the residuals (Moran's $I = 0.096$; $p=0.15$).

2.5 Discussion

This study investigated geographic disparities of diabetes prevalence and Diabetes Self-management Education (DSME) Program participation rates in Florida. Some previous studies have shown evidence of geographic disparities in both burden of diabetes and access to healthcare for individuals with diabetes in the United States (Barker et al., 2011; Lord et al., 2020; Ricci-Cabello et al., 2010; Shrestha, 2012; Walker et al., 2014, 2015). One of the ways that the CDC is trying to address these disparities is by providing diabetes preventive

Table 2.7: Univariable associations between county characteristics and clusters of Diabetes Self-management Education (DSME) program participation in Florida, 2010.

Predictor variable	Diabetes Self-management Education (DSME) Participations	
	Coefficient (95% CI[1])	***p*-value[2]**
Proportion of having normal and less than normal weight	-4.047 (-15.049, 6.954)	0.471
Proportion of having overweight	6.959 (-10.260, 24.178)	0.428
Proportion of being obese	0.745 (-8.991, 10.481)	0.881
Proportion of smokers	2.448 (-8.106, 13.001)	0.649
Proportion of heavy drinkers	-8.540 (-44.742, 27.662)	0.644
Proportion of doing exercise	3.909 (-8.936, 16.754)	0.551
Proportion of having overall good health	8.364 (-5.580, 22.308)	0.240
Proportion of having overall poor health	-8.363 (-22.307, 5.580)	0.240
Proportion of having limited walking capacity	0.805 (-13.671, 15.280)	0.913
Proportion of having high school or less education	-3.862 (-9.764, 2.039)	0.200
Proportion of having some college education	10.378 (-5.524, 26.275)	0.201
Proportion of having college education	2.967 (-3.238, 9.172)	0.349
Proportion of being White, non-Hispanic	3.884 (-4.439, 12.207)	0.360
Proportion of being Black, non-Hispanic	-3.212 (-14.739, 8.316)	0.585
Proportion of being Other, non-Hispanic	-11.689 (-43.154, 19.776)	0.467
Proportion of being Hispanic	-3.575 (-15.880, 8.731)	0.569
Proportion of being married	13.310 (-0.592, 27.212)	0.061
Proportion of being divorced/widowed/separated	-4.752 (-23.354, 13.851)	0.617
Proportion of being never married	-15.613 (-33.068, 1.841)	0.080
Proportion male	-14.158 (-34.871, 6.556)	0.180
Proportion female	14.158 (-6.556, 34.871)	0.180
Proportion with age 18 to 44 years	-2.758 (-10.663, 5.146)	0.494
Proportion with age 45 to 64 years	1.023 (-7.915, 9.973)	0.822
Proportion with age equal or greater than 65 years	2.985 (-6.480, 12.449)	0.537
Median household income (in $10,000)	0.768 (-0.170, 1.706)	0.109
Proportion of being unemployed	21.916 (-14.617, 58.450)	0.240
Proportion of having diabetes	3.375 (-22.100, 28.761)	0.794
Proportion that take insulin	2.522 (-5.229, 10.274)	0.524
Proportion that have diabetic complications (retinopathy)	-3.372 (-14.733, 7.989)	0.561
Proportion that have regular healthcare provider access	2.344 (-10.635, 15.322)	0.723
Proportion of rural population	-3.696 (-7.140, -0.253)	0.035
Proportion that have insurance coverage	-4.383 (-4.835, 13.601)	0.351
Proportion with age ≥25 years with a college degree*	2.651 (-3.037, 8.602)	0.383
Proportion below the federal poverty level*	-13.309 (-29.933, 3.314)	0.117

[1]Confidence interval
[2]Potential statistical significance was assessed using a liberal critical p=0.15

Table 2.8: Results of the final logistic model showing statistically significant predictors of clusters of Diabetes Self-management Education (DSME) participation at the county level in Florida, 2010.

Predictor variable	Odds Ratio	Coefficient (95% CI[1])	SE[2]	Wald Chi-Square	*p*-value[3]
Proportion of rural population	0.025	-3.696 (-7.140, -0.253)	1.757	4.426	0.035

[1]Confidence interval
[2]Standard error
[3]Statistical significance was assessed using a critical p=0.05

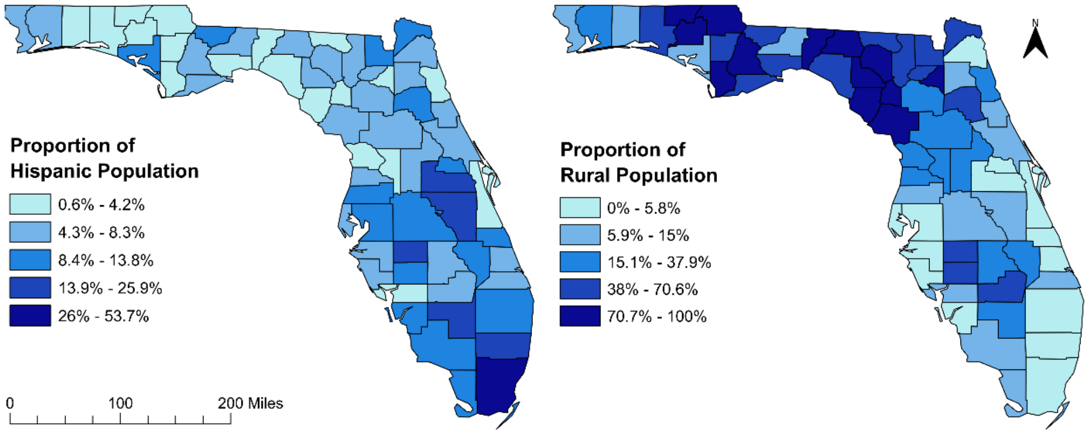

Figure 2.5: Distribution of significant predictors of Diabetes Self-management Education Program participation rates in Florida, 2010. Figure was created using the Free and Open Source Geographic Information System (GIS) software, QGIS.

programs (DPP). The DSME, which is run by the American Diabetes Association (ADA) designated centers, is one of the programs intended to educate diabetic patients on disease management. While DPP aim at reducing diabetes incidence in prediabetic populations, DSME targets to reduce diabetes related complications in diabetic populations (Shaul, 2018). However, DSME participation rates across the states are considerably low (Centers for Disease Control and Prevention, 2017a). In addition, DSME centers are not geographically distributed equitably resulting in potential disparities in DSME participation rates (Paul et al., 2018; Rutledge et al., 2017). Although disparities in DSME program availability have been investigated (Rutledge et al., 2017), no previous studies have investigated disparities of DSME participation rates and yet this information is critical for guiding resource allocation for DSME program implementation. The findings of the current study help to fill this gap and are useful in guiding evidence-based health planning and resource allocation in combating the diabetes problem.

Diabetes clusters identified in the north and central parts of Florida are consistent with findings by Barker *et al*., who reported that several counties of northern Florida were a part of the diabetes belt, an area of the southeast US where diabetes prevalence was significantly higher than the rest of the country (Barker et al., 2011). This is probably due to geographical differences in the distribution of socio-cultural and genetic factors (Barker et al., 2011). However, clusters of high diabetes prevalence identified in central Florida in the current study were not included in the diabetes belt of the study by Barker *et al*. This may be due to the fact that the study by Barker *et al*. used an arbitrary cut-off value of diabetes prevalence to define the diabetes belt (Barker et al., 2011). Their study defined counties with diabetes prevalence of ≥11% as belonging to the diabetes belt whereas our study has used a rigorous statistical approach to identify high prevalence diabetes clusters. Patterns of diabetes distribution similar to those of the current study were reported in another study which also identified several socioeconomic determinants (high levels of poverty, percentage of non-Hispanic black, obesity and physical inactivity) as significant predictors of the reported hotspots of diabetes prevalence in northern Florida (Shrestha, 2012).

Although high diabetes prevalence clusters were observed both in the northern and central parts of Florida, high DSME participation rate clusters were only observed in central Florida. It was concerning that seven counties in northern and central Florida had significant increases in diabetes prevalence during the study period and yet they had significant decreases in DSME participation rates during the same time period. This might be due to lack of DSME program facilities in the rural counties of northern Florida (Paul et al., 2018). This is supported by the findings of the OLS model used to investigate predictors of DSME participation rates which revealed that rural counties and those with a higher proportion of Hispanic population tended to have lower DSME participation rates. The findings of the logistic model investigating the predictors of a county being in a high DSME participation rate cluster almost mirrored those of the OLS model. The odds of a county being in a DSME high participation rate cluster was significantly lower for counties with higher percentages of rural residents compared to those with lower percentages of rural residents. In fact, the largest cluster of high DSME participation rates in 2010 was located in mid-east Florida where almost all of the counties were urban. These rural areas with high diabetes prevalence, but low DSME participation, are of significant concern as these areas could possibly contribute the most in economic burden of diabetes having a large diabetic population with more diabetes related complications.

The observed low DSME participation rates in counties with higher proportions of rural populations may be due to the lack of available DSME programs. There is evidence that rurality influences access to DSME more than socio-economic status such as poverty level (Graves et al., 2019). Thus, it is possible that rural areas of Florida have fewer DSME centers despite having a high burden of diabetes. This is consistent with the findings of a study by Paul *et al*., which reported that southeast regions of the US, including rural northern Florida, had higher diabetes prevalence but fewer DSME centers (Paul et al., 2018). Suffice it to say that despite having high prevalence of diabetes, Florida has inequities in distribution of DSME programs. Another study reported that almost two-thirds of rural counties of the US did not have a single DSME program (Rutledge et al., 2017).

The DSME participation may not depend on DSME program availability only. A study by Rutledge and co-workers reported that higher odds of having DSME centers (program availability) were associated with high percentage of diabetic and insured population, low percentage of population with high school education or less, and low unemployment rate (Rutledge et al., 2017). These factors could have also explained DSME participation if DSME program availability was the principal determinant of DSME participation rate. In the current study, although the proportion of insured population and those with high school education or less had significant univariable positive and negative associations with DSME participation rates, respectively, they were not significant in the final model. The reason for this is unclear but might be due to the fact that some other factors (e.g. availability of transport to DSME centers especially in rural areas) might be more important determinants of the DSME participation in Florida (Balamurugan et al., 2006; Rutledge et al., 2017; Testerman & Chase, 2018). Unfortunately, we did not have access to transportation data and therefore could not investigate this factor. Although counties with higher proportion of diabetic population are more likely to have DSME centers (Rutledge et al., 2017), the current study shows that DSME participation rate did not depend on whether a county has higher or lower proportion of diabetic population. This again implies that even if

DSME programs are available in rural Florida which had high diabetes prevalence, participation rate could be lower. It has been reported that health related program participation often depends on behavioral factors i.e., awareness, willingness to participate (Testerman & Chase, 2018). A New Jersey study also reported that DSME participation in certain counties did not always reflect DSME program availability (Santorelli et al., 2017). Thus, DSME participation is affected by not only program availability but also by acceptability, accessibility and other factors (Andersen, 1995; Graves, 2009). The implication of this is that the low DSME participation rates observed in rural areas of Florida could be the result of complex interactions between cultural, psychological, environmental, economic, and human resource factors such as transportation (Balamurugan et al., 2006; Rutledge et al., 2017), lack of specialists in rural areas, lack of diabetes educators (Powell et al., 2005), participants' literacy level, language barriers (Y.-H. Lee, 2020), lack of time, lack of childcare, participants' shame of illness, and participants lacking interest in their health (Testerman & Chase, 2018).

The significant negative association between county level DSME participation rates and proportion of Hispanic population suggests that racial disparities play a significant role in geographic disparities of DSME participation rates. Previous studies showed that Hispanics, Blacks, and Asians had low healthcare access compared to Whites with Hispanics facing the greatest barrier (National

Research Council, 2004). An individual level study reported that language barrier could significantly influence DSME participation (Martin et al., 2013; Testerman & Chase, 2018). In the United States, patients who attend DSME programs tend to be Caucasian and English-speaking (Martin et al., 2013). Although other studies have reported that counties with higher non-Hispanic Black population tended to have higher diabetes prevalence in Florida (Lord et al., 2020), there was no association between percentage of non-Hispanic black population and DSME participation rates in the current study. Rather, DSME participation rates in the current study tended to be lower in the southern Florida counties that had higher proportion of Hispanic population but lower diabetes prevalence. Thus, DSME participation rates in Florida did not depend on the burden of diabetes but might be more influenced by racial distribution. At the individual level, low DSME participation among Hispanics have been attributed to financial constraints, work schedule conflicts, and lack of transportation (Francis et al., 2014; Hu et al., 2013; Whittemore, 2007). Hence, family support, positive relationships with health care providers, and group support from DSME classes have been shown to increase DSME participation among Hispanics (Carbone et al., 2007; Francis et al., 2014).

2.5.1 Strength and Weakness

This is the first study investigating geographic disparities of DSME participation rates in Florida using rigorous statistical approaches. Understanding the relationship between diabetes burden and DSME participation rates and identifying areas with high diabetes burden but low DSME participation areas is crucial for guiding planning to reduce disparities in access to care for diabetic patients and improve DSME participation rates. However, this study is not without limitations. Data on diabetes and DSME participation were self-reported and so may be prone to reporting bias. The BRFSS does not categorize diabetes as either type 1 or type 2 and so this differentiation could not be made. However, 90-95% of all diabetes cases in the United States are type 2 diabetes (Centers for Disease Control and Prevention, 2017a). These limitations notwithstanding, the findings of this study provide useful information to guide health planning to reduce disparities in diabetes burden and DSME participation rates.

2.6 Conclusion

This study confirms geographic disparities of diabetes prevalence and DSME participation rates. It also identifies areas that have high diabetes prevalence but low DSME participation rates. These areas are of concern and will need specific attention in order to address the issue of disparities in healthcare accessibility of diabetic patients in Florida. The study has also demonstrated the usefulness of GIS and spatial epidemiologic/statistical approaches in investigating disparities in diabetes burden and DSME participation rates. Study findings are useful for guiding resource allocation geared towards reducing disparities and diabetes burden in Florida.

CHAPTER 3

Geographic Disparities and Temporal Changes of Diabetes-related Emergency Department Visit in Florida

Geographic disparities and temporal changes of diabetes-related emergency department visit in Florida

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A version of this chapter has been submitted to PloS One.

My contribution to this chapter included conceptualization of the research idea, data analysis, as well as writing and revision of the manuscript.

3.1 Abstract

Risks of diabetes-related Emergency Department (ED) visits in Florida increased by 54% between 2011 and 2016. However, little information is available on geographic disparities of ED visit risks and how these disparities changed over time in Florida and yet this information is important for guiding resource allocation for diabetes control programs. Therefore, the objectives of this study were to (a) investigate geographic disparities and temporal changes in diabetes-related ED visit risks in Florida and (b) identify predictors of geographic disparities in diabetes-related ED visit risks.

The ED data for the period between 2016 and 2019 were obtained from the Florida Agency for Healthcare Administration. Records of diabetes-related ED visits were extracted using the International Classification of Diseases (ICD)-10 codes. Monthly diabetes-related ED visit risks were computed and temporal changes were investigated using the Cochran-Armitage trend test. County-level diabetes-related ED visit risks were calculated and their geographic distributions were visualized using choropleth maps. Clusters of counties with high diabetes-related ED visit risks were identified using Kulldorff's circular and Tango's flexible spatial scan statistics. Predictors of diabetes-related ED visit risks were investigated using ordinary least square regression model. The geographic distributions of significant ($p \leq 0.05$) high-risk clusters and predictors of ED visit risks were displayed on maps.

There was a significant ($p<0.001$) increase in diabetes-related ED visit risks from 266 visits per 100,000 persons in January 2016 to 332 visits per 100,000 persons in December 2019. Clusters of high diabetes-related ED visit risks were identified in the northern and south-central parts of Florida. Counties with high percentages of non-Hispanic Black, current smokers, uninsured, and populations with diabetes had significantly higher diabetes-related ED visit risks, while counties with high percentages of married populations had significantly lower ED visit risks.

The study findings confirm geographic disparities of diabetes-related ED visit risks in Florida with high-risk areas observed in the rural northern and south-central parts of the state. Specific attention is required to address disparities in counties with high diabetes prevalence, high percentages of non-Hispanic Black, and uninsured populations. These findings are useful for guiding public health efforts geared at reducing disparities and improving diabetes outcomes in Florida.

3.2 Introduction

Diabetes is a chronic metabolic disease characterized by Fasting Plasma Glucose levels of $\geq$126 mg/dl (American Diabetes Association, 2020). The economic burden of diabetes is quite significant, as evidenced by the fact that the average healthcare expenditure of a patient with diabetes is 2.3 times higher than that of a patient without diabetes (Yang et al., 2018). Adults with poorly managed diabetes may suffer from short-term complications such as hypoglycemia, hyperglycemia, diabetic ketoacidosis, and long-term complications such as stroke, heart failure, retinopathy, neuropathy, nephropathy, and diabetic foot (Khan et al., 2022; Mayo Clinic, 2020). There is evidence that the risk of ED visits is higher among persons with diabetes (68 visits/100 persons) than the national average (40 visits/100 persons) (Centers for Disease Control and Prevention, 2021c, 2021d). In 2015, about 24% of all Emergency Department (ED) visits for patients aged 45 or over were made by those with diabetes (Hall et al., 2018; Washington et al., 2006). Out of 130 million ED visits in 2018 in the US, approximately 17 million visits were due to diabetes and diabetes-related complications.

Emergency departments play a vital role at the interface between the population and the healthcare system. Investigating patterns in the use of ED visits can help identify patterns of health resource utilization, identify disease trends and emerging threats, as well as assess the magnitude and management of disease problems (Kellermann et al., 2013). Previous studies reported that diabetes-related ED visits varied by age, race, ethnicity, income levels, and types of diabetes-related complications (Benoit et al., 2020; Ginde et al., 2008; Menchine et al., 2012; Washington et al., 2006). Not surprisingly, the southern states of the US, including Florida, have considerably higher diabetes-related ED visits than the rest of the country (Washington et al., 2006). A study identified this region as the diabetes belt, an area where diabetes prevalence was significantly higher than the rest of the US (Barker et al., 2011). However, diabetes management programs are not equitably distributed in this area and significant disparities exist in the use of available diabetes management programs (Khan et al., 2021). Lack of access to appropriate and timely diabetes care for some individuals with diabetes results in poor management of the condition leading to otherwise avoidable diabetes-related ED visits resulting in geographic disparities in ED visits (Barker et al., 2011; Lord et al., 2020; Ricci-Cabello et al., 2010; Shrestha, 2012; Walker et al., 2014, 2015). Identifying these disparities is important in guiding health planning for these patients. Although a study investigated geographic disparities in diabetes-related ED visits in the US at the regional level (Menchine et al., 2012), no such studies have been done at lower geographic scales and yet this information is important for guiding resource allocation to address the problem at the local level.

Diabetes is considered an Ambulatory Care Sensitive Condition (ACSC), a condition in which appropriate ambulatory/outpatient care can prevent complications and the need for ED visit and hospitalization (Agency for Healthcare Research and Quality, 2001). Therefore, disparities in diabetes-related ED visit may indicate differential outpatient care access, continuity, and quality (Johnson et al., 2012). Previous studies identified disparities in ED utilization among traditionally underserved groups such as Black, Hispanic, uninsured, and low-income patients (Hong et al., 2007; B. C. Sun et al., 2003). Since non-Hispanic Black and Hispanic populations represent almost half of the Florida population and there is evidence of 54% increase in diabetes-related ED visits in Florida between 2011 and 2016, investigating temporal changes and geographic disparities in diabetes-related ED visits is necessary for a better understanding of diabetes burden in Florida (Florida Department of Health, 2022; Florida Diabetes Advisory Council, 2019). Identifying areas with high diabetes-related ED visits in Florida could help identify areas with inadequate access to ambulatory care and poor quality of diabetes management (Dowd et al., 2014). This knowledge is important for planning programs targeted at improving access to primary diabetes care, reducing the burden of the condition and its complications, and improving population health. In addition, socioeconomic and demographic predictors of disparities in diabetes-related ED visits, if identified, would help guide resource allocation geared towards reducing disparities in availability of diabetes care as well as diabetes burden in Florida. Therefore, the objectives of this study were to: a) investigate geographic disparities and temporal changes in diabetes-related ED visit risks in Florida between 2016 and 2019; b) identify predictors of geographic disparities in diabetes-related ED visit risks in Florida.

3.3 Materials & Methods

3.3.1 Study Area

The study area encompassed the entire state of Florida and covered the time period from 2016 to 2019. As of 2020, Florida was the most populous state in the southeastern US with approximately 21.6 million people (Florida Department of Health, 2020d). Twenty two percent of Florida population was 0-19 years old, 31% was 20-44 years old, 26.1% was 45-64 years old, and the rest (20.9%) were 65 years old or older. Approximately half of the population was female. By race, White represented the majority (77.2%) of the population, Black were 17.0%, and all other races comprised the rest (5.8%). By ethnicity, 26.7% of the population was Hispanic-Latino while the rest were non-Hispanic (of any race) (Florida Department of Health, 2020d). The most urban and populous county was Miami-Dade (population: 2.9 million) located in the southern part of the state, while the most rural and least populous county was Lafayette (population: 8,721) located in the northern part of the state (Figure 3.1) (Florida Department of Health, 2016, 2020d). In total, Florida has 67 counties many of which are considered to be part of the diabetes belt which is an area located in the southeastern part of the US where diabetes prevalence is higher (11.7%) compared to the rest of the US (8.5%) (Barker et al., 2011).

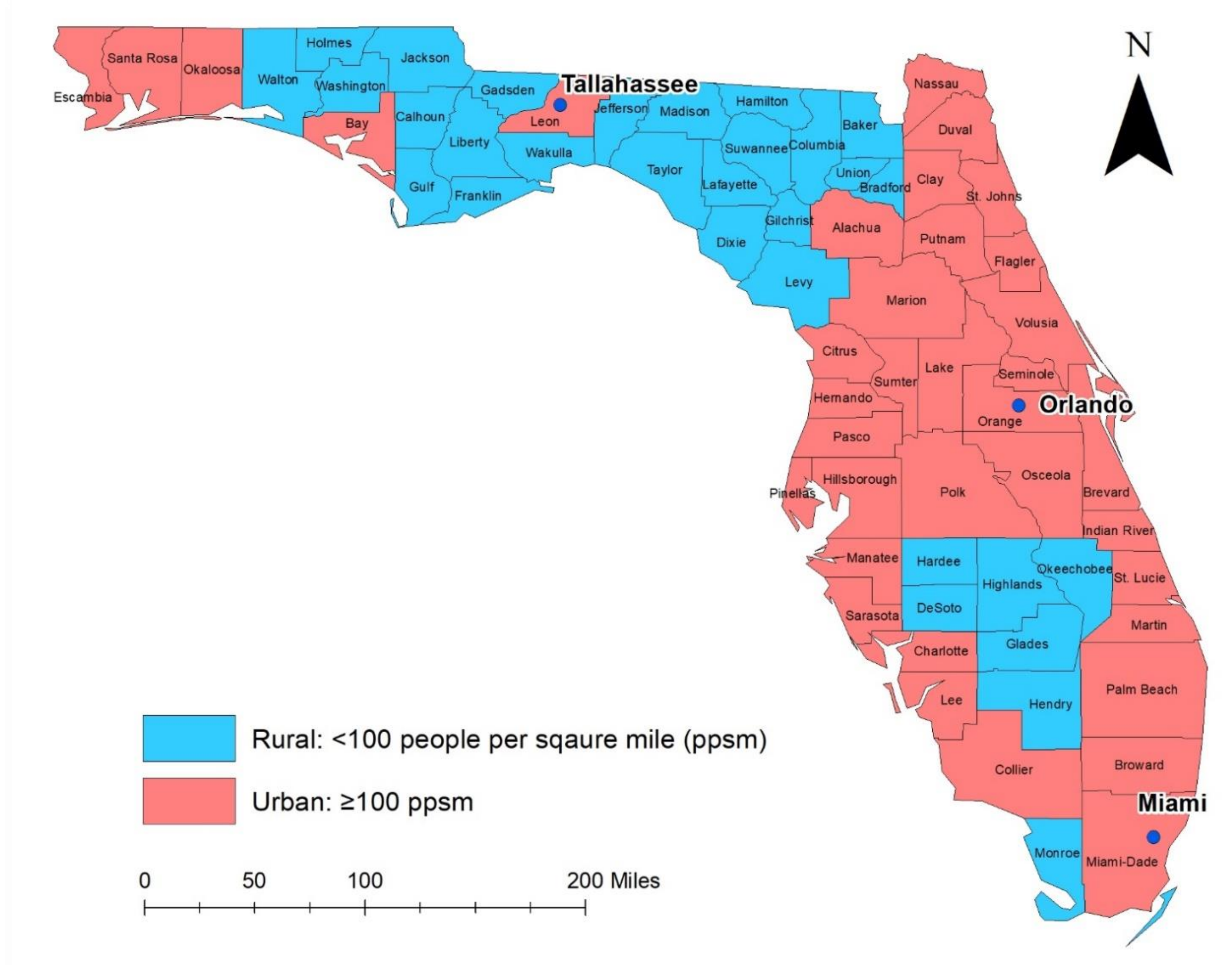

Figure 3.1: Florida map showing geographic distribution of rural and urban counties.

3.3.2 Data Sources

3.3.2.1 Emergency Department (ED) Data

Emergency Department (ED) data for the time period 2016-2019 were obtained from the Agency for Healthcare Administration, Florida. Records of ED visits due to diabetes and diabetes-related complications were extracted from the ED data using the following International Classification of Diseases (ICD)-10 codes listed in primary or secondary diagnoses: E08 (Diabetes mellitus due to underlying condition); E09 (Drug or chemical induced diabetes mellitus); E10 (Type 1 diabetes mellitus); E11 (Type 2 diabetes mellitus); and E13 (Other specified diabetes mellitus) (Kostick, 2012). Pregnancy-related diabetes and neonatal diabetes were excluded since both represent transient states of diabetes.

3.3.2.2 Socioeconomic, Demographic, Health, Environmental, and Cartographic Data

The 2017-2019 Behavioral Risk Factor Surveillance System (BRFSS) data, which contains questionnaire survey data for individuals aged 18 years or older, were obtained from the Florida Department of Health (FDH) (Florida Department of Health, 2020b). The following variables were extracted from the BRFSS: respondent's county of residence, race, gender, education, income, marital status, overall health status, Body Mass Index (BMI), level of daily physical activity, daily fruit and vegetable consumption, smoking and drinking habits, usage of tobacco, snuff, or e-cigarettes, healthcare accessibility, presence of comorbidities such as diabetes, heart disease, stroke, arthritis, kidney diseases, hypertension, hypercholesterolemia, and depression.

County-level percentages of population that are unemployed, lack access to healthy food and exercise opportunities, do not have food security, and live in rural areas were obtained from the County Health Rankings and Roadmap (CHRR) website (Robert Wood Johnson Foundation and The University of Wisconsin Population Health Institute, 2020). Additionally, county-level number of primary care physicians per 100,000 population and air pollution were extracted from the CHRR website. Data on total number of people per county were obtained from the population dashboard of the FDH (Florida Department of Health, 2020d). County-level age distribution of the population and household vehicle availability data were extracted from the 2015-2019 American Community Survey (ACS) 5-years average estimate (US Census Bureau, 2020). Cartographic boundary file for performing county-level geographic analyses was downloaded from the United States Census Bureau TIGER Geodatabase (United States Census Bureau, 2021).

3.3.3 Data Preparation & Descriptive Analysis

All data preparation and descriptive analyses were performed in SAS 9.4 (SAS Institute inc., 2017). Since the BRFSS data were collected using a complex survey design, all county-level estimates were calculated using SURVEYFREQ procedure of SAS specifying strata variable (_STSTR), cluster variable (_PSU), and sampling weight variable (_CNTYWT). Weighted county-level percentages of categorical variables were computed and presented in a table (Table 3.1). Annual county-level diabetes-related ED visit risks were also computed.

The Shapiro-Wilk test and QQ plot were used to assess the normality of continuous county-level variables. Normally distributed variables were summarized using mean and standard deviations while median and lower-upper quartiles were used for non-normally distributed variables. Temporal trends in monthly diabetes-related ED visit risks were investigated using the Cochran-Armitage trend test.

3.3.4 Spatial Analysis

3.3.4.1 Tango's Flexible Spatial Scan Statistics (FSSS)

Circular- and irregularly-shaped spatial clusters of high diabetes-related ED visit risks were investigated using Tango's flexible spatial scan statistics implemented in FlexScan 3.1.2 (Tango & Takahashi, 2005). Poisson probability model with restricted log likelihood (LLR) ratio (specifying $\alpha = 0.2$) and maximum cluster size set to 15 counties were used to ensure that identified clusters do not include counties with non-elevated risks. For statistical inference, 999 Monte Carlo replications and a critical p-value of 0.05 was used to assess statistical significance. Significant clusters were ranked based on their restricted LLR

Table 3.1: Summary statistics of variables considered as potential predictors of county-level diabetes-related emergency department visit risks in Florida, 2019.

Predictor variable	Mean	SD[1]	Median	IQR[2]	Minimum	Maximum
Percent with age less than 20 years*	21.68	3.40	21.70	4.20	8.30	29.50
Percent with age 20 to 44 years	29.98	5.20	30.80	6.50	13.90	41.50
Percent with age 45 to 64 years*	26.69	2.09	27.00	2.20	20.80	31.70
Percent with age ≥65 years*	21.64	7.73	20.10	8.40	11.60	56.70
Percent non-Hispanic White*	69.75	15.02	74.07	16.05	13.07	89.53
Percent non-Hispanic Black*	13.07	9.50	9.97	11.11	1.10	54.42
Percent Hispanic*	13.36	12.44	8.97	10.65	2.78	69.79
Percent non-Hispanic other races*	3.83	1.65	3.64	2.10	0.92	8.59
Percent male*	51.15	4.46	48.77	5.58	46.84	70.10
Percent female*	48.86	4.46	51.23	5.58	29.91	53.16
Percent of having less than high school education*	15.81	6.23	14.75	7.26	5.38	38.37
Percent of having high school education	35.23	7.11	35.00	12.03	19.88	54.82
Percent of having some college education*	29.89	4.54	30.83	7.39	17.57	35.55
Percent of having college education*	19.07	8.06	18.44	13.51	6.06	35.62
Percent that income less than 25k per year*	33.96	7.14	34.27	12.87	20.30	53.39
Percent that income 25k to 50k per year	27.88	4.21	28.36	5.58	20.55	40.20
Percent that income more than 50k per year	38.15	9.41	37.17	17.12	19.39	58.94
Percent unemployed*	3.48	0.64	3.40	0.70	2.10	5.80
Percent married	50.75	5.27	50.38	5.96	38.49	66.98
Percent divorced/widowed/separated	24.19	3.28	24.85	4.80	16.35	30.61
Percent never married or unmarried couple*	25.06	5.79	23.88	7.54	10.60	45.16
Percent of having overall poor health	22.56	4.86	22.59	7.48	8.59	33.13
Percent of having overall good health	77.44	4.86	77.41	7.48	66.88	91.41
Percent of being highly active*	34.53	5.61	33.78	7.08	24.35	54.60
Percent of being active	15.27	3.45	14.86	4.46	9.09	27.53
Percent of being insufficiently active	15.85	3.16	15.69	3.74	9.41	26.20

Table 3.1 Continued

Predictor variable	Mean	SD[1]	Median	IQR[2]	Minimum	Maximum
Percent of being inactive	34.35	6.63	33.58	11.26	22.67	51.23
Percent of having normal weight	29.72	5.27	29.55	6.70	19.43	43.93
Percent of being obese	32.46	6.06	32.24	8.29	18.19	48.06
Percent of being overweight	35.68	3.64	36.07	3.75	24.61	43.83
Percent of having less than normal weight	2.14	0.91	2.12	1.29	0.31	5.39
Percent that eat vegetables ≥once a day	82.05	4.75	82.56	5.90	66.58	93.33
Percent that eat fruits ≥once a day	60.50	5.77	60.85	8.29	49.11	72.77
Percent that lack access to healthy food*	9.33	5.74	9.00	6.00	0.00	31.00
Percent with food insecurity*	14.00	2.22	14.00	4.00	10.00	20.00
Percent with access to exercise opportunity*	68.94	24.52	77.00	36.00	10.00	100.00
Percent of being current smokers	19.14	5.09	18.49	6.98	11.03	32.41
Percent of being current tobacco or snuff user*	4.99	3.27	3.58	5.21	1.24	13.52
Percent of being current e-cigarette users*	5.73	1.84	5.72	2.22	2.00	13.15
Percent of being heavy drinkers	7.22	2.24	6.99	2.89	1.27	12.22
Percent that have no insurance coverage*	17.39	4.32	16.76	4.87	9.45	31.45
Percent that could not see a doctor in the last 12 months	16.42	3.01	16.03	4.59	9.49	21.93
Percent that have a personal doctor	73.65	5.12	74.39	7.14	57.61	86.03
Number of primary care physician per 100k population*	49.93	28.13	50.77	41.82	0.00	158.26
Percent of houses with no vehicle*	5.72	1.91	5.26	2.10	1.89	10.34
Percent of having diabetes	13.36	3.09	12.91	4.56	6.35	20.79
Average age of diabetes diagnosis	48.95	2.49	49.14	3.23	42.39	53.52
Percent of attending DSME	53.41	10.76	53.14	16.76	29.56	76.60
Percent of being depressed	17.77	3.26	17.86	3.86	10.32	24.70
Percent that have any disability	34.35	5.39	34.65	8.30	20.99	45.86
Percent of having kidney disease*	3.76	1.16	3.58	1.56	1.72	7.69
Percent that have regular checkup	76.11	3.88	76.09	5.09	63.19	89.08
Percent that take medications for high cholesterol	61.32	5.11	61.36	7.68	47.65	70.52

Table 3.1 Continued

Predictor variable	Mean	SD[1]	Median	IQR[2]	Minimum	Maximum
Percent that take medications for hypertension	78.95	4.07	78.83	5.00	67.32	89.25
Percent of having myocardial infarction or heart disease	5.65	1.48	5.72	2.05	2.55	8.97
Percent of having stroke	4.52	1.29	4.51	1.94	1.23	7.01
Percent of having arthritis	28.97	5.31	28.74	7.10	17.80	40.21
Percent that have high cholesterol	32.32	3.82	31.76	4.50	23.56	43.70
Percent that have hypertension	38.21	5.06	37.58	7.42	25.30	46.98
Percent of rural population*	37.50	32.26	23.77	59.04	0.02	100.00
Air quality (Average parts per million)*	7.52	0.91	7.70	1.30	5.20	9.10
Diabetes-related ED[3] visit risk*	4342.40	1447.00	3991.11	1498.00	1881.92	10176.10

[1]Standar deviation
[2]Interquartile range
[3]Emergency department
*Non-normally distributed variables

values. Clusters with diabetes-related ED visit risk ratios less than 1.2 were not reported to avoid reporting very low-risk clusters.

3.3.4.2 Kulldorff's's Circular Spatial Scan Statistics (CSSS)

Kulldorff's CSSS, implemented in SaTScan 9.6, was used to identify circular non-overlapping purely spatial high-risk clusters of diabetes-related ED visit risks. A discrete Poisson probability model specifying a maximum circular window size of 13.5% of population at risk was used in the analysis. The window size was set based on the population of Miami-Dade county, which has the largest population in Florida. This window size ensures that all counties have a chance of being in a cluster regardless of their population size. As for Tango's method, 999 Monte Carlo replications and a critical p-value of 0.05 were used to identify statistically significant clusters.

3.3.5 Predictors of Geographic Distributions of Diabetes-Related ED Visit Risks

To identify the predictors of county-level diabetes-related ED visit risks, a global ordinary least squares (OLS) regression model was built in SAS using county-level data obtained from the BRFSS, CHRR, FDH, and ACS (SAS Institute inc., 2017). This involved first assessing univariable associations between each of the potential predictors and log of county-level diabetes-related ED visit risks using a relaxed p-value of $\leq$0.15. Correlations among the potential predictors were assessed using Spearman's rank correlation coefficients. To avoid multicollinearity, only one of a pair of highly correlated variables ($r \geq 0.7$) was retained for assessment in the multivariable model. The decision of which variable of the pair to keep was determined using biological and statistical considerations. Variables that were significant potential predictors and not highly correlated were used to build the multivariable OLS model. The final main effects model was built using manual backward elimination approach specifying a critical p-value of ≤ 0.05. Confounding was assessed by running the model with and without a suspected confounder and assessing the changes in regression coefficients of variables in the model. A variable was kept in the final main effects model as a confounder if its removal from the model resulted in a change of 20% or more of the coefficients of any other variables in the model. Biologically meaningful two-way interaction terms were assessed and only the significant ones were kept in the final main effects model. Multicollinearity among variables in the final main effects model was assessed using Variance Inflation Factor (VIF). Variables with VIF >10 were considered collinear. Heteroskedasticity, normality, and spatial dependence of residuals were assessed using White test, Jarque-Bera test, and Robust Lagrange Multiplier (LM) test, respectively. Inverse distance spatial weight was used in the computation of the LM test.

3.3.6 Cartographic Displays

All cartographic displays were performed using ArcGIS v10.7 (Environmental Systems Research Institute (ESRI), 2018). The geographic distribution of diabetes-related ED visit risks and significant ($p \leq 0.05$) spatial clusters were displayed on maps. Critical intervals for choropleth maps were determined using Jenk's optimization classification scheme.

3.3.7 Ethics Approval

This study was reviewed by the University of Tennessee Institutional Review Board (Number: UTK IRB-20-05707-XM) and determined to be eligible for exempt review under 45 CFR 46.101. Category 4: Secondary research for which consent is not required. The study used anonymized secondary data provided to the investigators in such a manner that the identity of the human subjects cannot be ascertained directly or through identifiers linked to the subjects. The investigators did not contact the subjects and did not re-identify subjects.

3.4 Results

3.4.1 Temporal Pattern

Overall, diabetes-related ED visit risks in Florida increased significantly ($p<0.001$) from 266 visits per 100,000 persons in January 2016 to 332 visits per 100,000 persons in December 2019 (Figure 3.2). The highest diabetes-related ED visit risk (332 ED visits per 100,000 persons) was observed in December 2019, while

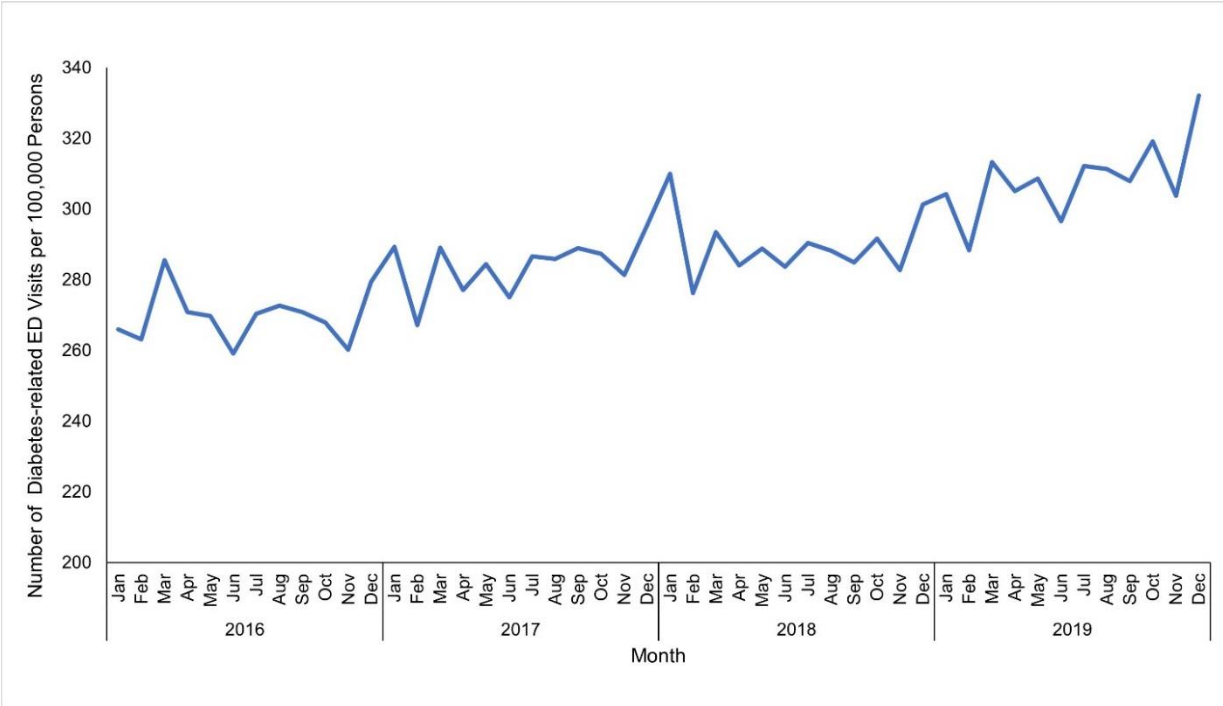

Figure 3.2: Temporal patterns of diabetes-related emergency department visit risks in Florida, January 2016-December 2019.

the lowest (259 ED visits per 100,000 persons) was in June 2016.

3.4.2 Spatial Distribution

County-level geographic distribution of diabetes-related ED visit risks varied across counties in Florida ranging from 1,448 to 10,211 visits per 100,000 persons (Figure 3.3). Overall, more than half of the counties had high diabetes-related ED visit risks (>3,385 ED visits per 100,000 persons) during the study period. Almost all counties in rural northern Florida, including the entire panhandle area up to the westernmost part of the state, had higher diabetes-related ED visits than counties in the southern part of the state (Figures 3.1 and 3.3). However, a few counties in the north-central portion had low ED visit risks in 2016 and 2017. Most of the counties in the central part of the state tended to have high diabetes-related ED visit risks, while low risks were consistently observed in the southernmost part and urban coastal areas during the study period (Figures 3.1 and 3.3).

3.4.3 Clusters of High Diabetes-Related ED Visit Risks

Consistent with high diabetes-related ED visit risks observed in the northern and central parts of Florida, significant ($p<0.05$) high diabetes-related ED visit risk clusters were identified in these areas (Figures 3.3, 3.4, and 3.5). Overall, numbers, sizes, and geographic locations of high diabetes-related ED visit risk clusters were almost consistent across years (Tables 3.2 and 3.3, Figures 3.4

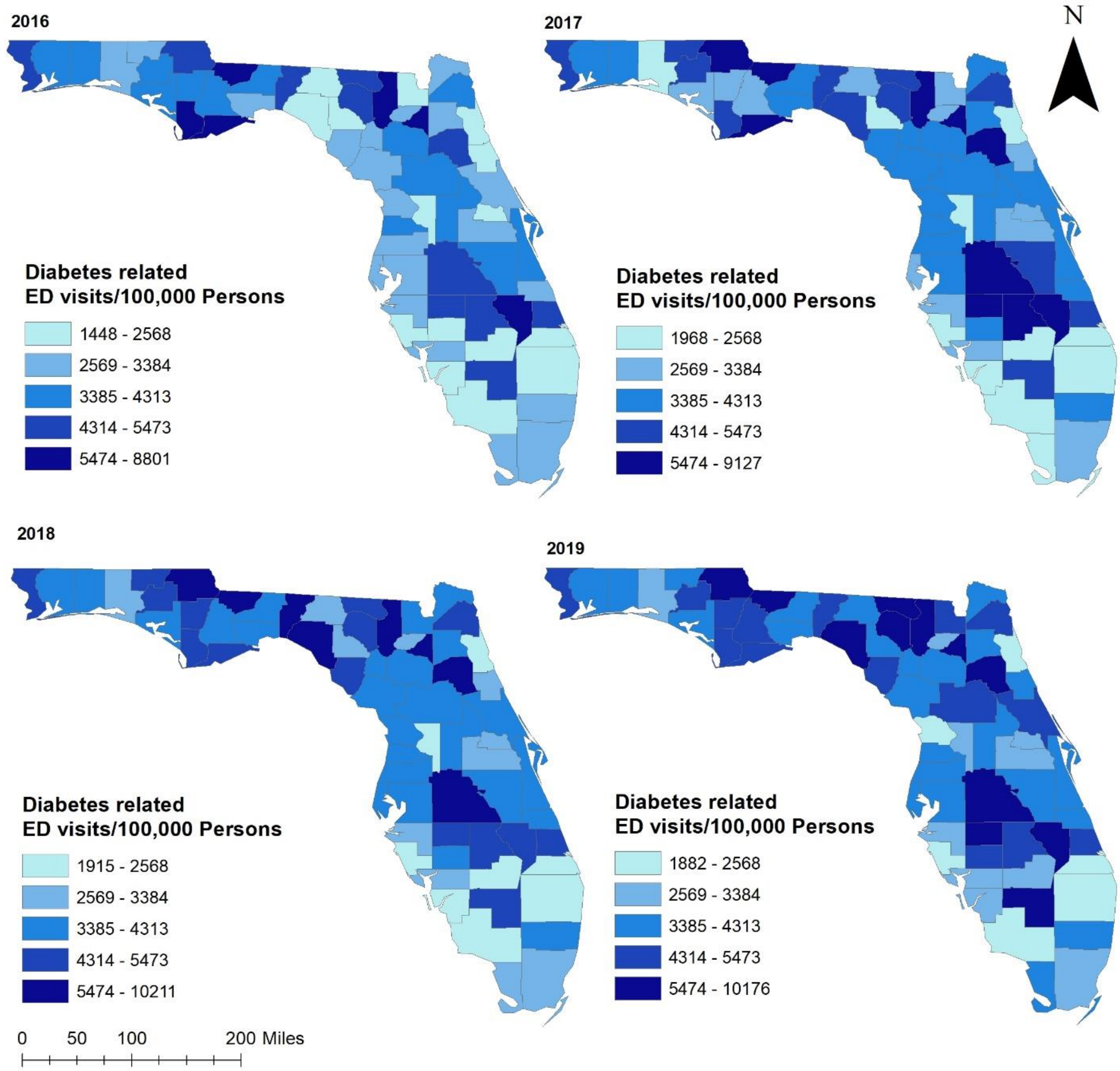

Figure 3.3: Geographic distribution of diabetes-related emergency department visit risks in Florida, 2016-2019.

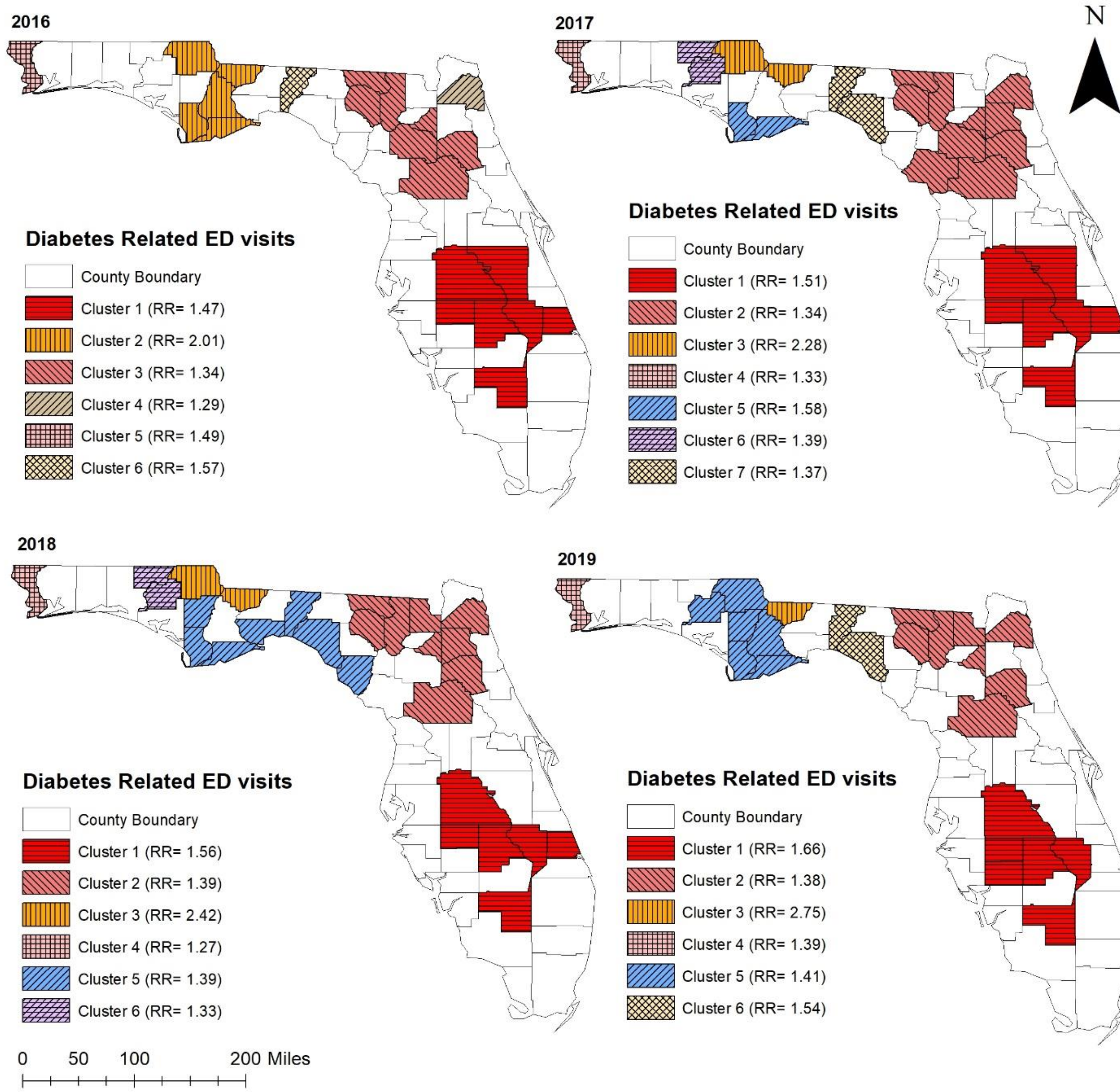

Figure 3.4: Spatial clusters of high diabetes-related emergency department visit risks identified in Florida using Tango's flexible spatial scan statistics, 2016-2019.

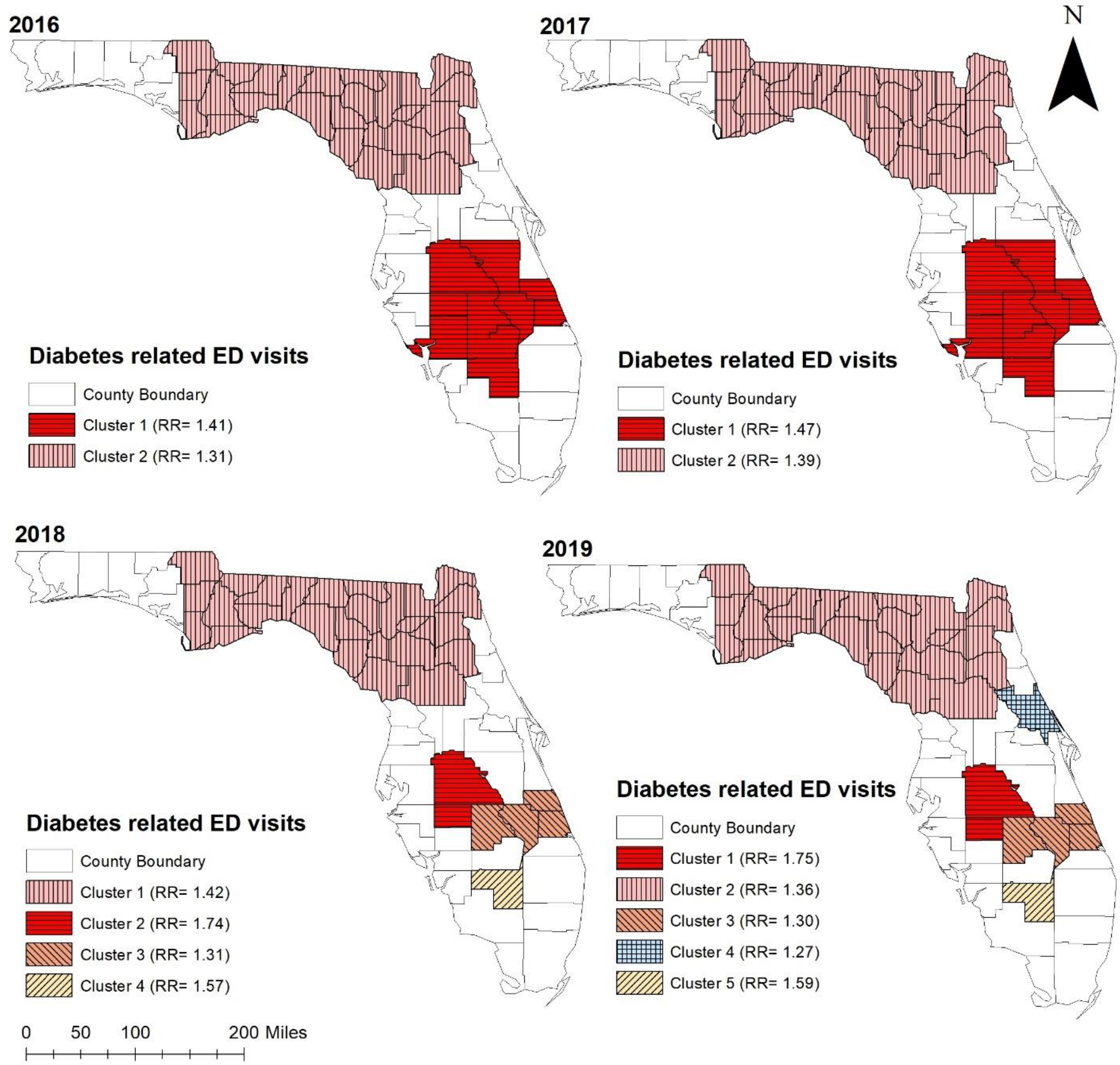

Figure 3.5: Spatial clusters of high diabetes-related emergency department visit risks identified in Florida using Kulldorff's circular spatial scan statistics, 2016-2019.

Table 3.2: Spatial clusters of high diabetes-related emergency department visit risks identified in Florida using Tango's flexible spatial scan statistics, 2016-2019.

Year	Cluster	Population	Observed ED[1] visits	Expected ED visits	No. of counties	RR[2]	*p*-value[3]
2016	Cluster 1	1,578,659	70,233	47,893	7	1.47	0.001
	Cluster 2	135,942	8,871	4,409	5	2.01	0.001
	Cluster 3	859,052	36,193	26,947	7	1.34	0.001
	Cluster 4	971,842	38,837	30,031	1	1.29	0.001
	Cluster 5	322,901	15,028	10,054	1	1.49	0.001
	Cluster 6	14,842	736	469	1	1.57	0.001
2017	Cluster 1	1,578,659	77,918	51,596	7	1.51	0.001
	Cluster 2	2,089,357	93,015	69,367	10	1.34	0.001
	Cluster 3	98,251	7,676	3,374	2	2.28	0.001
	Cluster 4	322,901	14,129	10,661	1	1.33	0.001
	Cluster 5	28,524	1,557	987	2	1.58	0.001
	Cluster 6	45,565	2,128	1,536	2	1.39	0.001
	Cluster 7	37,494	1,721	1,253	2	1.37	0.001
2018	Cluster 1	1,209,981	65,020	41,651	6	1.56	0.001
	Cluster 2	1,809,443	85,977	61,927	9	1.39	0.001
	Cluster 3	98,251	8,324	3,436	2	2.42	0.001
	Cluster 4	322,901	14,011	11,020	1	1.27	0.001
	Cluster 5	129,934	6,300	4,519	7	1.39	0.001
	Cluster 6	45,565	2,106	1,587	2	1.33	0.001
2019	Cluster 1	936,626	57,579	34,683	6	1.66	0.001
	Cluster 2	1,592,334	81,540	58,963	8	1.38	0.001
	Cluster 3	47,926	4,877	1,775	1	2.75	0.001
	Cluster 4	322,901	16,641	11,957	1	1.39	0.001
	Cluster 5	128,345	6,717	4,753	6	1.41	0.001
	Cluster 6	37,494	2,137	1,388	2	1.54	0.001

[1]Emergency department
[2]Risk ratio
[3]Statistical significance was assessed using a critical p = 0.05

Table 3.3: Spatial clusters of high diabetes-related emergency department visit risks identified in Florida using Kulldorff's circular spatial scan statistics, 2016-2019.

Year	Cluster	Population	Observed ED[1] visits	Expected ED visits	No. of counties	RR[2]	*p*-value[3]
2016	Cluster 1	1,846,525	81,070	59,761	11	1.41	<0.001
	Cluster 2	2,698,053	109,703	87,319	27	1.31	<0.001
2017	Cluster 1	1,886,441	90,568	64,295	11	1.47	<0.001
	Cluster 2	2,731,991	122,774	93,114	27	1.39	<0.001
2018	Cluster 1	2,759,367	129,329	95,906	27	1.42	<0.001
	Cluster 2	709,127	41,802	24,647	2	1.74	<0.001
	Cluster 3	601,631	27,223	20,911	4	1.31	<0.001
	Cluster 4	39,682	2,160	1,379	1	1.57	<0.001
2019	Cluster 1	716,081	45,210	26,516	2	1.75	<0.001
	Cluster 2	2,798,463	134,345	103,625	27	1.36	<0.001
	Cluster 3	609,119	29,056	22,555	4	1.30	<0.001
	Cluster 4	539,563	25,178	19,980	1	1.27	<0.001
	Cluster 5	40,089	2,353	1,484	1	1.59	<0.001

[1]Emergency department
[2]Risk ratio
[3]Statistical significance was assessed using a critical p = 0.05

and 3.5). The primary high-risk clusters were consistently identified in the south-central portion of the state and mainly included rural counties (Hardee, Highlands, Okeechobee, and Hendry) (Figures 3.1 and 3.4). Similarly, several small high-risk clusters located across the panhandle area included only rural counties. However, a high-risk cluster was identified in the rural-urban interface of north-central Florida and included both rural and urban counties. Although high-risk clusters were not identified in the southern and coastal urban areas, a single county high-risk cluster (Escambia) was consistently identified in the westernmost urban part of the state (Figures 3.1 and 3.4). Similar to the findings of Tango's FSSS, Kulldorff's CSSS identified significant high diabetes-related ED visit risk clusters in the panhandle area, north-central, and central portions of the state and included mostly rural counties. However, unlike Tango's FSSS, larger but fewer clusters were identified by Kulldorff's CSSS (Tables 3.2 and 3.3, Figures 3.4 and 3.5).

3.4.4 Predictors of Diabetes-Related ED Visit Risks

Tables 3.4 and 3.5 show the results of the univariable and final multivariable models used to investigate associations between county-level sociodemographic variables and county-level diabetes-related ED visit risks, respectively. Based on the final multivariable model, there were significant positive associations between county-level diabetes-related ED visit risk and percentages of population who were non-Hispanic Black ($p = 0.002$), current smokers ($p<0.001$), had diabetes

Table 3.4: Univariable associations between county characteristics and diabetes-related emergency department visit risks in Florida, 2019.

Predictor Variable	Coefficient (95% CI[1])	p-value[2]
Percent with age less than 20 years	0.034 (0.011, 0.056)	0.004
Percent with age 20 to 44 years	0.020 (0.005, 0.034)	0.009
Percent with age 45 to 64 years	-0.015 (-0.053, 0.024)	0.448
Percent with age ≥65 years	-0.014 (-0.024, -0.005)	0.005
Percent non-Hispanic White	-0.005 (-0.010, 0.0001)	0.060
Percent non-Hispanic Black	0.015 (0.007, 0.023)	<0.001
Percent Hispanic	-0.001 (-0.008, 0.005)	0.721
Percent non-Hispanic other races	-0.017 (-0.065, 0.032)	0.500
Percent male	0.018 (0.0001, 0.035)	0.048
Percent female	-0.018 (-0.035, -0.0001)	0.048
Percent of having less than high school education	0.034 (0.024, 0.044)	<0.001
Percent of having high school education	0.022 (0.012, 0.032)	<0.001
Percent of having some college education	-0.037 (-0.052, -0.021)	<0.001
Percent of having college education	-0.025 (-0.033, -0.018)	<0.001
Percent that income less than 25k per year	0.029 (0.020, 0.037)	<0.001
Percent that income 25k to 50k per year	0.024 (0.005, 0.042)	0.012
Percent that income more than 50k per year	-0.021 (-0.028, -0.014)	<0.001
Percent unemployed	0.191 (0.074, 0.308)	0.002
Percent married	-0.024 (-0.038, -0.010)	0.001
Percent divorced/widowed/separated	0.020 (-0.004, 0.044)	0.102
Percent never married or unmarried couple	0.013 (-0.0001, 0.027)	0.052
Percent of having overall poor health	0.040 (0.027, 0.053)	<0.001
Percent of having overall good health	-0.040 (-0.053, -0.027)	<0.001
Percent of being highly active	-0.030 (-0.042, -0.017)	<0.001
Percent of being active	-0.029 (-0.052, -0.007)	0.011
Percent of being insufficiently active	-0.006 (-0.032, 0.019)	0.624
Percent of being inactive	0.031 (0.021, 0.040)	<0.001
Percent of having normal weight	-0.029 (-0.043, -0.016)	<0.001
Percent of being obese	0.036 (0.026, 0.046)	<0.001
Percent of being overweight	-0.039 (-0.059, -0.019)	<0.001
Percent of having less than normal weight	0.013 (-0.076, 0.102)	0.768
Percent that eat vegetables ≥once a day	-0.019 (-0.036, -0.003)	0.020
Percent that eat fruits ≥once a day	-0.022 (-0.035, -0.010)	<0.001
Percent that lack access of healthy food	0.009 (-0.005, 0.023)	0.188
Percent with food insecurity	0.089 (0.060, 0.118)	<0.001
Percent that have access of exercise opportunity	-0.004 (-0.008, -0.001)	0.006
Percent of being current smokers	0.026 (0.012, 0.040)	<0.001
Percent of being current tobacco or snuff user	0.033 (0.010, 0.056)	0.006

Table 3.4 Continued

Predictor Variable	Coefficient (95% CI[1])	p-value[2]
Percent of being current ecig users	-0.005 (-0.049, 0.039)	0.822
Percent of being heavy drinkers	-0.054 (-0.087, -0.020)	0.002
Percent that have no insurance coverage	0.040 (0.024, 0.056)	<0.001
Percent that could not see a doctor in the last 12 months	0.044 (0.020, 0.069)	<0.001
Percent that have a personal doctor	-0.010 (-0.025, 0.006)	0.219
Number of primary care physician per 100k population	-0.005 (-0.008, -0.003)	<0.001
Percent of houses with no vehicle	0.057 (0.017, 0.097)	0.005
Percent of having diabetes	0.048 (0.025, 0.071)	<0.001
Average age of diabetes diagnosis	-0.041 (-0.072, -0.011)	0.009
Percent of attending DSME	-0.011 (-0.018, -0.004)	0.002
Percent of being depressed	0.012 (-0.013, 0.036)	0.343
Percent that have any disability	0.027 (0.014, 0.041)	<0.001
Percent of having kidney disease	0.075 (0.008, 0.142)	0.029
Percent that have regular checkup	-0.017 (-0.037, 0.003)	0.098
Percent that take medications for high cholesterol	0.006 (-0.010, 0.022)	0.448
Percent that take medications for hypertension	-0.014 (-0.033, 0.006)	0.169
Percent of having myocardial infarction or heart disease	0.044 (-0.009, 0.097)	0.103
Percent of having stroke	0.083 (0.024, 0.142)	0.006
Percent of having arthritis	0.001 (-0.014, 0.017)	0.853
Percent that have high cholesterol	-0.009 (-0.030, 0.012)	0.385
Percent of having hypertension	0.018 (0.003, 0.033)	0.022
Percent of rural population	0.004 (0.002, 0.006)	<0.001
Air quality (Average parts per million)	0.085 (-0.001, 0.171)	0.053

[1]Confidence interval
[2]Statistical significance was assessed using a critical p = 0.15

Table 3.5: Results of ordinary least square regression model showing predictors of diabetes-related emergency department visit risks in Florida, 2019.

Predictor Variable	Coefficient (95% CI[1])	SE[2]	t-value	p-value[3]	VIF[4]
Percent non-Hispanic Black	0.010 (0.004, 0.016)	0.003	3.240	0.002	1.296
Percent of having diabetes	0.033 (0.014, 0.051)	0.009	3.560	<0.001	1.229
Percent that have no insurance coverage	0.019 (0.005, 0.033)	0.007	2.720	0.008	1.381
Percent current smokers	0.019 (0.008, 0.030)	0.005	3.520	<0.001	1.147
Percent married	-0.014 (-0.027, -0.003)	0.006	-2.460	0.017	1.496

[1]Confidence interval
[2]Standard error
[3]Statistical significance was assessed using a critical $p = 0.05$
[4]Variance Inflation Factor

($p<0.001$), and had no insurance coverage ($p = 0.008$). However, percentage of population that were married ($p = 0.017$) had significant negative association with diabetes-related ED visit risk. There was no evidence of non-normality ($p = 0.107$), heteroscedasticity ($p = 0.057$),or multicollinearity (VIF <10). In addition, no spatial dependence of residuals was identified based on the results of the robust Lagrange Multiplier tests for lag ($p = 0.928$) and error ($p = 0.585$).

Geographic distributions of the significant predictors of diabetes-related ED visit risks are shown in Figure 3.6. Counties in the central and eastern panhandle rural area tended to have high percentages of population that were non-Hispanic Black, current smokers, had diabetes, and had no insurance coverage. These counties overlapped with many counties with high diabetes-related ED visit risks (Figures 3.1, 3.3, and 3.6). On the other hand, counties in the southernmost urban area of the state had relatively low diabetes-related ED visit risks but tended to have high percentages of non-Hispanic Black and low percentages of married, current smokers, and those with diabetes. Although counties with high percentages of population with diabetes were concentrated in the mid to south-central part of the state, these counties had low percentages of population with health insurance coverage (Figures 3.1, 3.3, and 3.6).

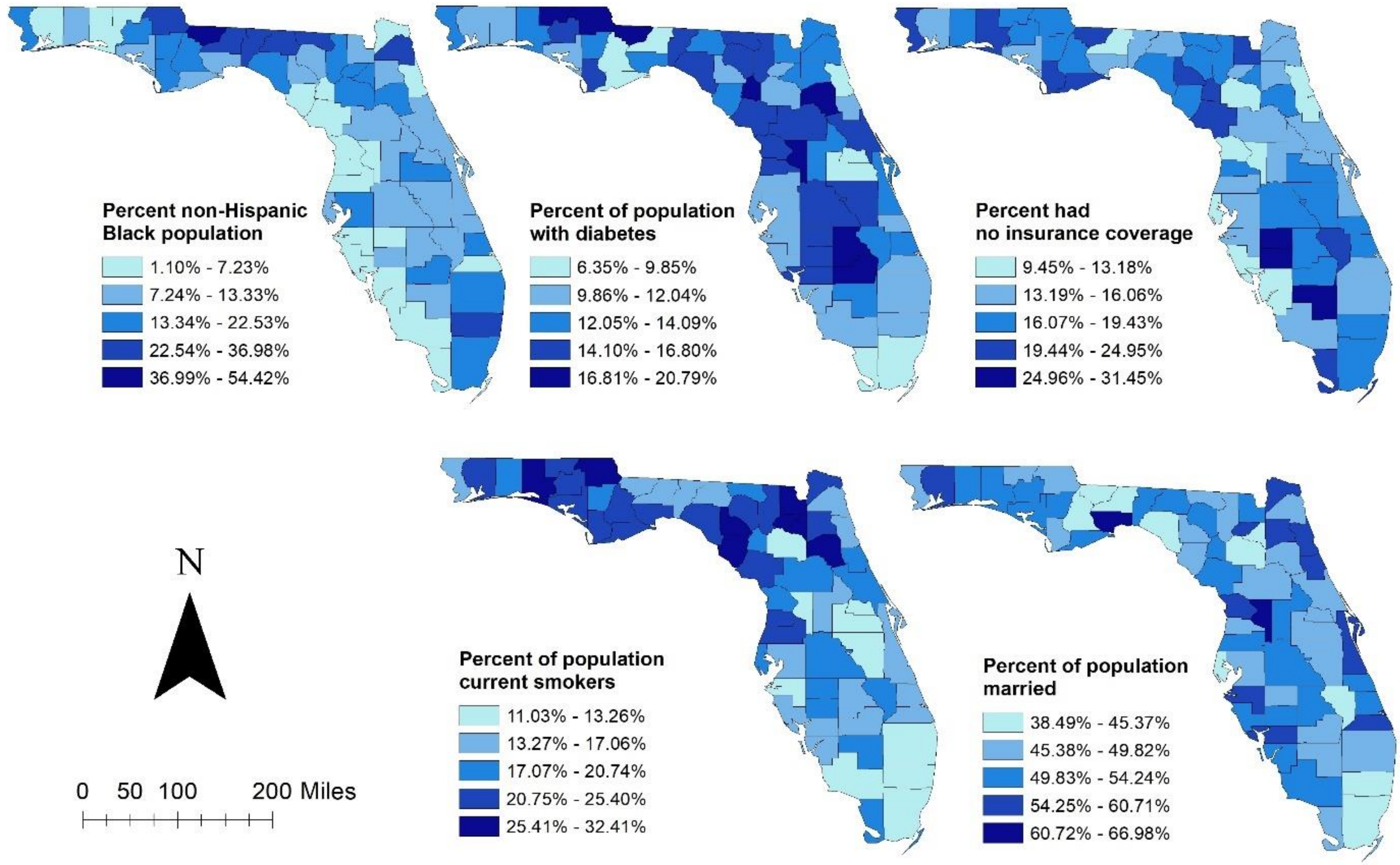

Figure 3.6: Distribution of significant predictors of diabetes-related emergency department visit risks in Florida, 2016-2019.

3.5 Discussion

This study investigated geographic disparities and temporal changes of diabetes-related ED visit risks in Florida from 2016 to 2019. Although diabetes prevalence and healthcare access for individuals with diabetes vary across counties in Florida (Barker et al., 2011; Lord et al., 2020; Ricci-Cabello et al., 2010), little is known about the geographic disparities of diabetes-related ED visits and yet this information is critical for improving the health and quality of life of populations with diabetes. The findings of the current study help to fill this gap and are important for guiding healthcare planning targeted at reducing disparities in diabetes-related ED visit risks in Florida. In addition, this study investigated sociodemographic, environmental, and lifestyle-related predictors of diabetes-related ED visit risks. The results are useful for guiding evidence-based resource allocation aimed at guiding the implementation of control programs and reducing the burden of diabetes in Florida.

The observed high diabetes-related ED visit risks in the northern and southcentral parts of Florida may be related to access to diabetes care in these more rural communities. Evidence suggests that individuals living in rural areas tend to be poor and lack health insurance coverage (Khan et al., 2023; Rural Health Information Hub, 2022). Since diabetes is an ambulatory-care sensitive condition, getting regular primary care could substantially reduce ED visit risks and improve quality of life (Agency for Healthcare Research and Quality, 2001).

However, access to primary care for diabetes could be limited in rural areas due to the lack of health insurance coverage, which could result in higher diabetes-related ED visit risks. This is evidenced by the findings of this study because counties with high percentages of populations with no health insurance coverage had high diabetes-related ED visit risks. Additionally, a study by Khan et al. reported that rural Florida had lower Diabetes Self-Management Education (DSME) Program Participation rates than urban areas due to fewer DSME centers and limited accessibility to DSME program (Khan et al., 2021). The DSME program was developed to educate diabetes patients on disease management and reduce diabetes-related complications and ED visit risks (Powers et al., 2015). However, lack of health insurance coverage among rural populations in northern Florida might have prevented access to DSME programs, lowered DSME participation rates, and, therefore, resulting in higher ED visit risks.

Another reason of the high diabetes-related ED visit risks in northern Florida could be the high percentages of non-Hispanic Black populations in those areas. The findings of this study showed a significant positive association between counties with high percentages of non-Hispanic Black populations and ED visit risks, which is consistent with the findings of previous studies (Taylor et al., 2019; Uppal et al., 2022). A study by Uppal et al. reported that diabetes-specific ED use among non-Hispanic Black patients was approximately 3 times higher than among non-Hispanic White patients. This is because non-Hispanic Black patients have higher risks of diabetes-related complications such as albuminuria, retinopathy, lower extremity amputation, end-stage renal disease (ESRD), and worse glycemic control than their non-Hispanic White counterparts (Canedo et al., 2018; Osborn et al., 2013). Moreover, minority populations such as non-Hispanic Black or Hispanic are less likely to receive recommended diabetes preventive care (Taylor et al., 2019) and have low participation in DSME programs (Khan et al., 2021).

The significant negative association between county-level diabetes-related ED visit risks and percentages of married population identified in this study suggests that social support from marriage relationships may be beneficial for diabetes patients. Previous studies reported lower diabetes morbidity and mortality among married persons compared to their unmarried counterparts (Kposowa et al., 2021). This is because married persons are more likely to get better social and mental support (Umberson, 1992), lead healthy lifestyles (Eng, 2005), and have better medication adherence and diabetes management (Ahmed et al., 2017; Gelaw et al., 2014).

The finding that counties with high percentages of current smokers had high diabetes-related ED visit risks is consistent with reports from other previous studies (U.S. Department of Health and Human Services, 2010, 2014). .

According to a report published by the Centers for Disease Control and Prevention (CDC), people who smoke and have diabetes are more likely to develop serious health problems from diabetes such as heart disease, kidney diseases, retinopathy, peripheral neuropathy, and lower leg amputations (Centers for Disease Control and Prevention, 2022b; U.S. Department of Health and Human Services, 2010). Moreover, these people tend to have trouble with insulin dosing and managing diabetes (U.S. Department of Health and Human Services, 2010, 2014).

The findings of this study showed that counties with high diabetes prevalence tended to have high diabetes-related ED visit risks even after adjusting for sociodemographic factors and healthcare access. According to a report published by the CDC, persons with diabetes have a higher risk of ED visits (68 visits/100 persons) than the national average (40 visits/100 persons) (Centers for Disease Control and Prevention, 2021c, 2021d). This is because diabetes can affect many organ systems due to poor blood sugar control capacity resulting in hypo- or hyperglycemia. Hypoglycemia could lead to shock and death, while long-term hyperglycemia could be responsible for many complications such as neuropathy, nephropathy, retinopathy, stroke, cardiovascular, and peripheral vascular diseases (Deshpande et al., 2008) which may result in high ED visit risks.

3.5.1 Strengths and limitations

This is the first study investigating geographic disparities of diabetes-related ED visits in Florida using rigorous statistical approaches. Identifying areas with high diabetes-related ED visit risks is crucial for guiding resource allocation and improving access to primary diabetes care. This study also investigated sociodemographic predictors of diabetes-related ED visits in Florida, the findings of which are important for guiding programs aimed at reducing disparities in the availability of diabetes care and improving the health of populations with diabetes in Florida.

3.6 Conclusions

This study confirms presence of geographic disparities of diabetes-related ED visit risks in Florida with high-risk areas being observed in the rural northern and southcentral parts of the state. Lack of healthcare access, high diabetes prevalence, low socioeconomic status, and certain demographic factors were identified as significant predictors of high diabetes-related ED visit risks. These findings are useful for guiding public health efforts geared at reducing disparities and improving diabetes outcomes in Florida.

CHAPTER 4

Prevalence and Predictors of Stroke among Individuals with Prediabetes and Diabetes in Florida

Prevalence and predictors of stroke among individuals with prediabetes and diabetes in Florida

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A version of this chapter has been published in BMC Public Health.

Citation:

Khan MM, Roberson S, Reid K, Jordan M, Odoi A. Prevalence and predictors of stroke among individuals with prediabetes and diabetes in Florida. BMC Public Health. 2022;22:1–11. doi:10.1186/s12889-022-12666-3.

My contribution to this chapter included conceptualization of the research idea, data analysis, as well as writing and revision of the manuscript.

4.1 Abstract

The prevalence of both prediabetes and diabetes have been increasing in Florida. These increasing trends will likely result in increases of stroke burden since both conditions are major risk factors of stroke. However, not much is known about the prevalence and predictors of stroke among adults with prediabetes and diabetes and yet this information is critical for guiding health programs aimed at reducing stroke burden. Therefore, the objectives of this study were to estimate the prevalence and identify predictors of stroke among persons with either prediabetes or diabetes in Florida.

The 2019 Behavioral Risk Factor Surveillance System (BRFSS) survey data were obtained from the Florida Department of Health and used for the study. Weighted prevalence estimates of stroke and potential predictor variables as well as their 95% confidence intervals were computed for adults with prediabetes and diabetes. A conceptual model of predictors of stroke among adults with prediabetes and diabetes was constructed to guide statistical model building. Two multivariable logistic models were built to investigate predictors of stroke among adults with prediabetes and diabetes.

The prevalence of stroke among respondents with prediabetes and diabetes were 7.8% and 11.2%, respectively. The odds of stroke were significantly ($p \le 0.05$) higher among respondents with prediabetes that were ≥45 years old

(Odds ratio [OR]=2.82; 95% Confidence Interval [CI]= 0.74, 10.69), had hypertension (OR=5.86; CI=2.90, 11.84) and hypercholesterolemia (OR=3.93; CI=1.84, 8.40). On the other hand, the odds of stroke among respondents with diabetes were significantly ($p \leq 0.05$) higher if respondents were non-Hispanic Black (OR=1.79; CI=1.01, 3.19), hypertensive (OR=3.56; CI=1.87, 6.78) and had depression (OR=2.02; CI=1.14, 3.59).

Stroke prevalence in Florida is higher among adults with prediabetes and diabetes than the general population of the state. There is evidence of differences in the importance of predictors of stroke among populations with prediabetes and those with diabetes. These findings are useful for guiding health programs geared towards reducing stroke burden among populations with prediabetes and diabetes.

4.2 Background

Stroke occurs when there is lack of blood supply to a part of the brain due to either blockage of a vessel from a blood clot (ischemic stroke) or bleeding from a ruptured vessel (hemorrhagic stroke) (American Stroke Association, 2021a). It is the 5th leading cause of death in the US and more than 600,000 people in the country experience first time stroke each year (Centers for Disease Control and Prevention, 2020a, 2020d). It is also the leading cause of long-term serious disability and costs $34 billion each year in the US (Centers for Disease Control and Prevention, 2020d).

Both prediabetes and diabetes are major risk factors of stroke. Individuals with diabetes have two times higher risk of experiencing a stroke than those that do not have the condition (American Stroke Association, 2021b). Prediabetes, on the other hand, is a modest risk factor for first time stroke but doubles the risk of recurrent stroke (Fonville et al., 2014; M. Lee et al., 2012). More than 30 million people in the US have diabetes (Centers for Disease Control and Prevention, 2020a); the prevalence of the condition has doubled over the last 20 years and is projected to double or triple by 2050. Similarly, the prevalence of prediabetes in the US has been increasing. Currently, almost a third of the US adult population (88 million) have prediabetes (Centers for Disease Control and Prevention, 2020f).

There is evidence that about 23-53% of stroke patients have prediabetes, while 14-46% have diabetes (Fonville et al., 2014; Mijajlovic et al., 2017). The increasing trends in prediabetes and diabetes prevalence will likely result in higher stroke burden in the future. Given the changes in prediabetes and diabetes landscape, the American Heart Association (AHA) and American Diabetes Association (ADA) have jointly acknowledged the need to better understand the epidemiology of stroke among individuals that have prediabetes and diabetes so as to better guide stroke prevention and control programs (American Diabetes Association et al., 1999; Buse et al., 2007; Fox et al., 2015). However, not much is known about the epidemiology of stroke in these populations because previous studies have mainly focused on investigating the epidemiology of stroke in the general population (Boehme et al., 2017). A study conducted in Europe investigated risk factors of stroke among individuals with diabetes, but it did not include the US population (Giorda et al., 2007). To our knowledge, no study has investigated risk factors of stroke among individuals with prediabetes.

Florida is one of the states in the diabetes belt, an area with a higher burden of the condition than the rest of the country (Barker et al., 2011). The burden of diabetes has been increasing in Florida as evidenced by the fact that diabetes prevalence has increased from 5.2% in 1995 to 12.6% in 2018 (Florida Diabetes Advisory Council, 2019). This increase will likely result in an increase of Florida's stroke burden. Understanding stroke epidemiology among individuals with prediabetes and diabetes is important for guiding evidence-based health planning and service provision to control stroke burden and improve quality of care for stroke patients. Therefore, the objectives of this study were to estimate the prevalence and identify predictors of stroke among persons with prediabetes and diabetes in Florida.

4.3 Materials & Methods

4.3.1 Study Area

This study was conducted in Florida, the most populous state in the southeastern US with a population of approximately 21.2 million. With 20.4% of the population composed of senior citizens (≥65 years old), Florida has the second-highest number of the elderly population in the US (Himes & Kilduff, 2019). The rest of the population is distributed as follows: 0-19 years old (22.1%), 20-34 years old (19.1%), 35-44 years old (12.1%), 45-54 years old (12.9%), and 55-64 years old (13.4%). Approximately 51% of the population is female. The majority (77.3%) of the population is White, 16.9% is Black, while all other races comprise 5.8% of the population. By ethnicity, Hispanic-Latino comprises 26.3% of the population, while the rest is non-Hispanic (Florida Department of Health, 2019b).

4.3.2 Data Source, Study Population, and Variable Selection

The 2019 Behavioral Risk Factor Surveillance System (BRFSS) survey data, obtained from the Florida Department of Health (FDOH), were used in this study. The BRFSS is a telephone survey designed to collect data on individual risk behaviors, chronic health conditions, and preventive health practices from non-institutionalized adults 18 years of age and older. Records of two groups of respondents were extracted from the 2019 BRFSS data, respondents with prediabetes and those with diabetes. The above classification is based on the respondents having been told by a doctor that they had prediabetes or diabetes.

No distinction was made between type 1 and type 2 diabetes as this information was not captured in the BRFSS survey. Pregnancy diabetes was excluded since it is a temporary condition. Stroke status was determined based on the respondent's report of having been told by a doctor that they had a stroke. The survey did not gather information on types of strokes (ischemic and hemorrhagic) and, therefore, no distinction was made in types of strokes.

A conceptual model of predictors of stroke among respondents with prediabetes and diabetes was constructed based on biological knowledge, literature review, and questions asked in the BRFSS survey (Figure 4.1). The list of variables considered for investigation as potential predictors or confounders is shown in Table 4.1. The potential predictors considered for investigation can be broadly classified into sociodemographic factors, risk behaviors, and chronic health conditions. Sociodemographic factors investigated included age, sex, race, marital status, income, education, and health insurance coverage. Risk behaviors investigated were cigarette smoking and drinking habits, physical activity, Body Mass Index (BMI), as well as fruit and vegetable consumption. Chronic health conditions assessed included hypercholesterolemia (high blood cholesterol), hypertension, arthritis, and kidney disease.

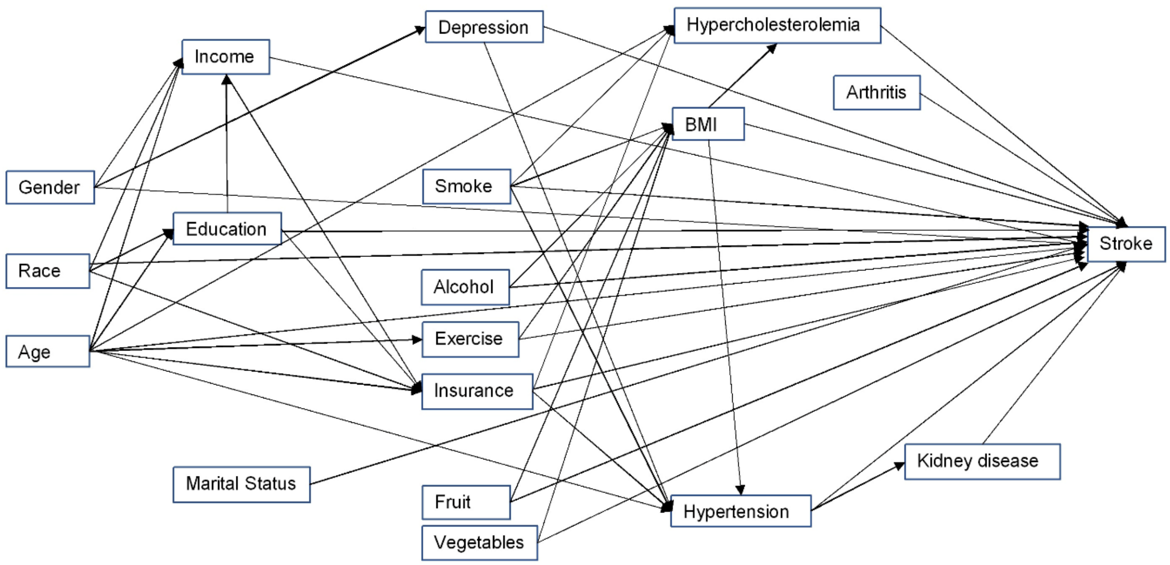

Figure 4.1: Conceptual model representing predictors of stroke among adults who reported having either prediabetes or diabetes.

Table 4.1: Demographic, health, and lifestyle characteristics among adults who reported having either prediabetes or diabetes.

Characteristic	Categories	Prediabetes (n[a] = 1608)		Diabetes (n[a] = 2680)	
		n[a]	Weighted % (95% CI[b])	n[a]	Weighted % (95% CI[b])
Age					
	65 years or over	785	35.29 (31.00, 39.59)	1,663	53.03 (48.88, 57.17)
	45 to 65 years	611	44.66 (39.44, 49.88)	858	38.84 (34.60, 43.08)
	18 to 44 years	212	20.05 (15.30, 24.79)	159	8.13 (6.07, 10.19)
Sex					
	Male	711	45.81 (40.45, 51.16)	1,274	52.54 (48.43, 56.65)
	Female	897	54.19 (48.84, 59.55)	1,406	47.46 (43.35, 51.57)
Race					
	Other races (non-Hispanic)	99	3.87 (2.30, 5.43)	158	3.98 (2.29, 5.68)
	Hispanic	144	22.18 (16.95, 27.40)	264	22.63 (18.52, 26.73)
	Black (non-Hispanic)	166	14.40 (10.12, 18.68)	383	18.67 (15.28, 22.07)
	White (non-Hispanic)	1,199	59.55 (54.26, 64.95)	1,875	54.71 (50.85, 58.59)
Ever smoked cigarettes					
	Yes	788	46.37 (41.12, 51.62)	1,295	49.01 (44.83, 53.18)
	No	742	53.63 (48.38, 58.88)	1,220	50.99 (46.82, 55.17)
Heavy drinking habit					
	Yes	91	6.24 (4.11, 8.38)	65	3.01 (1.77, 4.25)
	No	1,401	93.76 (91.62, 95.89)	2,411	96.99 (95.75, 98.23)
Income level					
	<$15,000	167	9.84 (6.56, 13.11)	324	14.63 (10.87, 18.37)
	$15,000- <$25,000	263	20.29 (16.14, 24.43)	566	25.75 (21.63, 29.86)
	$25,000- <$35,000	180	13.82 (9.91, 17.73)	299	14.36 (10.12, 18.61)
	$35,000- <$50,000	221	13.86 (10.45, 17.27)	288	13.41 (10.43, 16.39)
	≥$50,000	476	42.19 (36.29, 48.10)	601	31.86 (27.59, 36.13)

Table 4.1 Continued

Characteristic	Categories	Prediabetes (n[a] = 1608)		Diabetes (n[a] = 2680)	
		n[a]	Weighted % (95% CI[b])	n[a]	Weighted % (95% CI[b])
Education					
	College	461	21.97 (18.25, 25.70)	640	18.28 (15.78, 20.77)
	Some college	497	35.42 (30.00, 40.83)	764	28.65 (24.84, 32.47)
	High school	502	30.99 (26.27, 35.71)	846	31.09 (27.30, 34.88)
	<High school	147	11.62 (8.19, 15.05)	409	21.98 (18.01, 25.95)
Depression					
	Yes	434	25.19 (21.02, 29.36)	628	20.03 (16.72, 23.34)
	No	1,164	74.81 (70.64, 78.98)	2,028	79.97 (76.66, 83.28)
Level of physical activity					
	Inactive	502	34.33 (29.12, 39.53)	1,070	38.39 (34.50, 42.28)
	Insufficiently active	165	11.58 (7.46, 15.70)	283	16.89 (12.85, 20.92)
	Active	185	16.79 (12.53, 21.05)	265	15.73 (12.04, 19.41)
	Highly active	575	37.30 (31.95, 42.66)	725	29.00 (25.41, 32.59)
Consume fruit(s)					
	≥1 per day	859	65.94 (61.06, 70.81)	1,341	60.09 (55.89, 64.28)
	<1 per day	567	34.06 (29.19, 38.94)	979	39.91 (35.72, 44.11)
Consume vegetable(s)					
	≥1 per day	1,120	76.94 (71.48, 82.41)	1,773	75.03 (70.96, 79.10)
	<1 per day	265	23.06 (17.59, 28.52)	471	24.97 (20.90, 29.04)
Insurance					
	Yes	653	80.48 (74.83, 86.13)	831	84.13 (77.84, 90.41)
	No	150	19.52 (13.87, 25.17)	163	15.87 (9.59, 22.16)
Hypercholesterolemia					
	Yes	848	48.37 (42.97, 53.76)	1,569	59.68 (55.41, 63.96)
	No	676	51.63 (46.24, 57.03)	979	40.32 (36.04, 44.59)

Table 4.1 Continued

Characteristic	Categories	Prediabetes (n[a] = 1608)		Diabetes (n[a] = 2680)	
		n[a]	Weighted % (95% CI[b])	n[a]	Weighted % (95% CI[b])
Hypertension					
	Yes	974	53.73 (48.34, 59.11)	2,009	72.06 (68.02, 76.09)
	No	632	46.27 (40.89, 51.66)	664	27.94 (23.91, 31.98)
Body Mass Index (BMI) (kg/m^2)					
	Underweight	25	2.14 (0.31, 3.97)	14	0.27 (0.03, 0.51)
	Normal (18.5-24.9)	252	17.41 (12.93, 21.90)	381	17.16 (13.44, 20.89)
	Overweight (25-29.9)	518	31.99 (27.34, 36.64)	833	35.99 (31.70, 40.28)
	Obese (≥30)	675	48.46 (42.88, 54.04)	1,200	46.58 (42.27, 50.88)
Marital Status					
	Never married	209	14.54 (10.82, 18.26)	268	11.56 (9.17, 13.95)
	Separated/divorced/widowed	634	30.47 (25.57, 35.38)	1,185	35.70 (31.81, 39.59)
	Married	765	54.95 (49.74, 60.24)	1,227	52.74 (48.58, 56.90)
Arthritis					
	Yes	787	38.73 (34.05, 43.42)	1,373	49.02 (44.87, 53.17)
	No	812	61.27 (56.58, 65.95)	1,292	50.98 (46.83, 55.13)
Chronic kidney disease					
	Yes	87	5.79 (2.80, 8.78)	343	12.07 (9.37, 14.77)
	No	1,513	94.21 (91.22, 97.20)	2,314	87.93 (85.23, 90.63)
Stroke					
	Yes	142	7.77 (5.25, 10.28)	361	11.16 (8.64, 13.69)
	No	1,462	92.23 (89.72, 94.75)	2,300	88.84 (86.32, 91.36)

[a]CI: Confidence intervals
[b]n: Unweighted sample size

4.3.3 Data Preparation and Descriptive Analyses

Race/ethnicity was re-coded into four categories (Non-Hispanic White, Non-Hispanic Black, Hispanic, and Other). The “Other” category included non-Hispanic Asian, American Indian/Alaskan Native, or all other races not listed above. Age was categorized into 18-44 years, 45-64 years, and 65 years or older and marital status was classified into married; divorced, widowed, or separated; and never married. Since the BRFSS data were collected using a complex survey design, a weight variable (created by the US Centers for Disease Control and Prevention [CDC]) was used in all analyses to ensure that the estimates are generalizable to all Florida adults. Descriptive analyses were conducted in SAS using SURVEY codes (SAS Institute inc., 2017) specifying strata variable (_STSTR), cluster variable (_PSU) and a sampling weight variable (_LLCPWT). Weighted percentage and 95% confidence intervals (95% CI) were calculated for all categorical variables.

4.3.4 Predictors of Stroke among Population with Prediabetes and Diabetes

Two multivariable logistic regression models were built to investigate predictors of stroke among respondents with prediabetes (model 1) and those with diabetes (model 2). The process of model building was similar in both models. The model building process involved first assessing univariable associations between each potential predictor and the outcome (stroke among either prediabetes [for model

1] or diabetes [for model 2] respondents) using a liberal p-value of ≤ 0.20. To avoid multicollinearity in subsequent multivariable models to be built, two-way Spearman rank correlation analyses were performed on all variables that showed significant association (based on relaxed $p \leq 0.20$) in the univariable analyses. Only one of a pair of highly correlated variables ($r > 0.7$) was considered for assessment in the subsequent multivariable models. The choice of which of a pair of highly correlated potential predictors to be assessed in the multivariable models was based on biological and statistical considerations. Manual backward elimination procedures were then used to fit the final weighted multivariable models setting the p-values for removal at ≤ 0.05. Confounders were assessed using changes in regression coefficients of variables in the models when the models were run with and without suspected confounders. If removal of a suspected confounding variable resulted in a change of 20% or more of any of the other variables in the models, then the variable was retained in the models as a confounder regardless of its statistical significance. Variables that had either significant association with the outcome or confounding effect were retained in the final main-effects models. Age was forced in the models due to a priori belief that it was a confounder. Biologically meaningful two-way interaction terms of the variables were then assessed with the aim of keeping significant ones in the final models. Odds ratios and 95% confidence intervals (95% CI) were computed for all predictors in the final main-effects models. Goodness-of-fit of the models were assessed using the Hosmer-Lemeshow test (Hosmer et al., 1988). All statistical analyses were performed in SAS 9.4 (SAS Institute inc., 2017).

4.3.5 Ethics Approval

This study was reviewed by the University of Tennessee Institutional Review Board (Number: UTK IRB-20-05707-XM) and determined to be eligible for exempt review under 45 CFR 46.101. Category 4: Secondary research for which consent is not required. The study used anonymized secondary data provided to the investigators in such a manner that the identify of human subjects cannot be ascertained directly or through identifiers linked to the subjects. The investigators did not contact the subjects and did not re-identify subjects.

4.4 Results

4.4.1 Prevalence Estimates

The study included a total of 16,959 survey respondents, of whom 9.5% (1,608) and 15.8% (2,680) had been told by a doctor that they had prediabetes and diabetes, respectively. Table 4.1 shows the demographic, health, and lifestyle characteristics of respondents that had prediabetes and diabetes. Most of the respondents with prediabetes were between 45 and 65 years old (44.7%), female (54.2%), non-Hispanic White (59.6%), and married (55.0%). The majority of them had an annual income of ≥$50,000 (42.2%), some college education (35.4%), and health care coverage (80.5%). Regarding risk behaviors, respondents were mostly non-smokers (53.6%), did not have heavy drinking habits (93.8%), and reported consuming fruits (66.0%) and vegetables (77%) ≥once a day. In addition, most respondents reported having no depression (74.8%) and being highly active in doing physical exercises (37.3%). Almost half of the respondents with prediabetes reported being obese (48,5%), having hypercholesterolemia (49.4%) and hypertension (53.7%). Thirty-eight percent of the respondents had arthritis, while a few had chronic kidney diseases (5.8%).

Respondents with diabetes were predominantly ≥65 years old (53%), male (52.5%), non-Hispanic White (54.7%), and married (52.7%). Thirty-one percent of the respondents had high school education and 31.9% reported earning ≥$50,000 annually. Unlike respondents with prediabetes, most of those with diabetes had hypercholesterolemia (59.7%), hypertension (72.3%), and were physically inactive (38.4%). Similar to the respondents with prediabetes, the majority of those with diabetes were obese (46.6%), non-smokers (51.0%), did not have heavy drinking habits (97.0%), had healthcare coverage (84.1%), and consumed fruits (60.1%) and vegetables (75.0%) ≥once a day. The percentage of stroke among respondents that had prediabetes and diabetes was 7.8% and 11.2%, respectively.

4.4.2 Univariable Associations

Table 4.2 shows the univariable (unadjusted) associations of each of the predictors with stroke among respondents with prediabetes and diabetes in

Table 4.2: Univariable associations of potential predictors of stroke among adults with prediabetes and diabetes in Florida

Characteristic	Categories	Respondents with prediabetes		Respondents with diabetes	
		Unadjusted Odds Ratio (95% CI[a])	p-value	Unadjusted Odds Ratio (95% CI[a])	p-value
Age					
	65 years or over	5.57 (1.52, 20.41)	<0.001	1.56 (0.55, 4.40)	0.418
	45 to 65 years	12.61 (3.68, 43.24)		1.99 (0.66, 5.97)	
	18 to 44 years	Reference		Reference	
Sex					
	Male	1.56 (0.79, 3.10)	0.200	1.32 (0.81, 2.14)	0.266
	Female	Reference		Reference	
Race					
	Other races (non-Hispanic)	2.08 (0.69, 6.24)		0.49 (0.24, 1.04)	
	Hispanic	0.66 (0.21, 2.08)	0.320	1.17 (0.54, 2.56)	0.027
	Black (non-Hispanic)	0.50 (0.12, 2.10)		1.87 (1.04, 3.38)	
	White (non-Hispanic)	Reference		Reference	
Ever smoked cigarettes					
	Yes	1.42 (0.69, 2.91)	0.340	1.55 (0.92, 2.63)	0.103
	No	Reference		Reference	
Heavy drinking habit					
	Yes	0.56 (0.13, 2.38)	0.430	0.75 (0.19, 3.00)	0.687
	No	Reference		Reference	
Income level					
	<$15,000	0.78 (0.28, 2.21)		2.26 (0.91, 5.62)	
	$15,000- <$25,000	1.01 (0.37, 2.76)		1.98 (1.01, 3.89)	
	$25,000- <$35,000	3.64 (1.22, 10.86)	0.069	2.05 (0.72, 5.87)	0.038
	$35,000- <$50,000	1.87 (0.64, 5.49)		0.78 (0.35, 1.77)	
	≥$50,000	Reference		Reference	

Table 4.2 Continued

Characteristic	Categories	Respondents with prediabetes		Respondents with diabetes	
		Unadjusted Odds Ratio (95% CI[a])	p-value	Unadjusted Odds Ratio (95% CI[a])	p-value
Education					
	College	0.41 (0.12, 1.34)		0.71 (0.31, 1.60)	
	Some college	0.39 (0.14, 1.12)	0.260	0.65 (0.30, 1.42)	0.751
	High school	0.38 (0.14, 1.04)		0.68 (0.31, 1.49)	
	<High school	Reference		Reference	
Depression					
	Yes	2.22 (1.08, 4.59)	0.030	2.07 (1.18, 3.63)	0.012
	No	Reference		Reference	
Level of physical activity					
	Inactive	1.49 (0.64, 3.45)		1.22 (0.67, 2.24)	
	Insufficiently active	0.37 (0.10, 1.33)	0.178	0.54 (0.24, 1.21)	0.183
	Active	0.98 (0.30, 3.23)		1.09 (0.38, 3.13)	
	Highly active	Reference		Reference	
Consume fruit(s)					
	≥1 per day	0.71 (0.34, 1.50)	0.366	1.21 (0.71, 2.05)	0.481
	<1 per day	Reference		Reference	
Consume vegetable(s)					
	≥1 per day	1.94 (0.81, 4.62)	0.136	0.85 (0.45, 1.62)	0.622
	<1 per day	Reference		Reference	
Insurance					
	Yes	0.70 (0.29, 1.67)	0.417	1.31 (0.37, 4.67)	0.675
	No	Reference		Reference	
Hypercholesterolemia					
	Yes	5.40 (2.57, 11.35)	<0.001	1.82 (1.04, 3.16)	0.035
	No	Reference		Reference	

Table 4.2 Continued

Characteristic	Categories	Respondents with prediabetes		Respondents with diabetes	
		Unadjusted Odds Ratio (95% CI[a])	p-value	Unadjusted Odds Ratio (95% CI[a])	p-value
Hypertension					
	Yes	7.33 (3.64, 14.78)	<0.001	3.78 (2.15, 6.67)	<0.001
	No	Reference		Reference	
Body Mass Index (BMI) (kg/m^2)					
	Under weight (<18.5)	0.73 (0.15, 3.58)		8.08 (1.27, 51.40)	
	Normal (18.5-24.9)	Reference	0.181	Reference	0.072
	Overweight (25-29.9)	2.02 (0.70, 5.83)		0.75 (0.37, 1.53)	
	Obese (≥30)	0.94 (0.33, 2.73)		0.98 (0.48, 2.02)	
Marital Status					
	Never married	0.87 (0.28, 2.72)	0.379	1.03 (0.46, 2.31)	0.954
	Separated/divorced/widowed	1.62 (0.77, 3.42)		1.09 (0.63, 1.89)	
	Married	Reference		Reference	
Arthritis					
	Yes	2.38 (1.17, 4.83)	0.017	1.58 (0.95, 2.64)	0.078
	No	Reference		Reference	
Chronic kidney disease					
	Yes	3.10 (0.89, 10.75)	0.075	2.36 (1.14, 4.87)	0.020
	No	Reference		Reference	

[a]CI: Confidence Intervals

Florida. The following variables had potentially significant ($p \leq 0.20$) simple/univariable associations with stroke among individuals with prediabetes: age, sex, income, depression, physical activity, vegetable consumption, hypercholesterolemia, hypertension, BMI, arthritis, and chronic kidney disease. All the above variables, except age, sex, and vegetable consumption, also had potentially significant ($p \leq 0.20$) associations with stroke among individuals with diabetes. Additionally, race and ever smoking cigarettes were significantly associated with stroke among individuals with diabetes but not among those with prediabetes.

4.4.3 Predictors of Stroke among Respondents with Prediabetes and Diabetes

The results of the final multivariable logistic regression models are presented in Table 4.3. Significant predictors of the odds of stroke among respondents with prediabetes were age, hypertension, and hypercholesterolemia. The odds of stroke among individuals 45-65 years old with prediabetes were 2.82 times [95% Confidence Interval (CI): 0.74, 10.69] higher than among those who were 18-44 years old while that among individuals ≥65 years with prediabetes were even higher [Odds Ratio (OR)=4.90; 95% CI: 1.38, 17.45]. The odds of stroke among individuals with prediabetes that also had hypertension were also higher (OR=5.86; 95% CI: 2.90, 11.84) than those among individuals that had prediabetes but not hypertension. Similarly, the odds of stroke among individuals

Table 4.3: Final multivariable logistic regression models showing predictors of stroke among adults with prediabetes and diabetes.

Characteristic	Categories	Respondents with prediabetes (model 1)		Respondents with diabetes (model 2)	
		Adjusted Odds Ratio (95% CI[a])	**p-value**	**Adjusted Odds Ratio (95% CI[a])**	**p-value**
Age					
	65 years or over	4.90 (1.38, 17.45)	0.032	1.68 (0.56, 5.05)	0.352
	45 to 65 years	2.82 (0.74, 10.69)		2.19 (0.69, 6.97)	
	18 to 44 years	Reference		Reference	
Hypertension					
	Yes	5.86 (2.90, 11.84)	<0.001	3.56 (1.87, 6.78)	<0.001
	No	Reference		Reference	
Hypercholesterolemia					
	Yes	3.93 (1.84, 8.40)	<0.001		
	No	Reference			
Race					
	Hispanic			1.23 (0.56, 2.70)	0.025
	Black (non-Hispanic)			1.79 (1.01, 3.19)	
	Other races (non-Hispanic)			0.42 (0.18, 0.96)	
	White (non-Hispanic)			Reference	
Depression					
	Yes			2.02 (1.14, 3.59)	0.016
	No			Reference	

[a]CI: Confidence Interval

that had prediabetes as well as hypercholesterolemia were 3.93 (95% CI: 1.84, 8.40) times higher than among individuals that had prediabetes but not hypercholesterolemia.

None of the significant predictors of stroke among individuals with prediabetes, except hypertension, was significantly associated with stroke among individuals with diabetes. The odds of stroke among individuals with diabetes that also had hypertension were 3.56 times (95% CI: 1.87, 6.78) higher than the odds of stroke among individuals that had diabetes but normal blood pressure. In addition, non-Hispanic Black (OR= 1.79, 95%CI: 1.01, 3.19) and depressed (OR= 2.02, 95% CI: 1.14, 3.59) individuals with diabetes had higher odds of stroke compared to non-Hispanic White and non-depressed individuals with diabetes, respectively. Although age was not a significant predictor of stroke among individuals with diabetes, it was retained in the final model because of a priori knowledge that it is a confounder. It is worth noting that non-Hispanic individuals of other races (OR=0.42, 95% CI: 0.18, 0.96) had significantly lower odds of stroke than non-Hispanic White among individuals with diabetes.

4.5 Discussion

This study investigated the prevalence and predictors of stroke among adults who reported having either prediabetes or diabetes in Florida. The percentages of stroke among adults with prediabetes (7.8%) and diabetes (11.2%) were higher than among the general population of Florida (3.6%) in 2019 (Florida Department of Health, 2021). No previous studies have investigated predictors of stroke among adults with prediabetes and diabetes and yet this information is critical for guiding health programs aimed at reducing stroke burden in Florida.

The identification of hypertension as a common predictor of stroke among adults with prediabetes and diabetes in this study is consistent with the findings from previous studies (American Heart Association, 2016; American Stroke Association, 2021c; Centers for Disease Control and Prevention, 2020e). According to a report by the AHA, hypertension increases risk of stroke by weakening arteries and weakened arteries are more likely to burst or clog resulting in hemorrhagic or ischemic stroke, respectively (American Heart Association, 2016). Evidence suggests that persons with prediabetes and diabetes have damaged blood vessels and compromised functionalities of heart and kidney due to higher than normal blood glucose levels. Compromised kidney functions increase blood volume and again decrease the stretching capacity of blood vessels (Dresden, 2019; Ohishi, 2018). As a result, adults with prediabetes and diabetes are more likely to experience stroke if they also have hypertension.

Previous studies reported age as a non-modifiable risk factor of stroke among both males and females (American Stroke Association, 2018; Kelly-Hayes, 2010; Yousufuddin & Young, 2019). Similar to these findings, this study identified higher odds of stroke among individuals ≥45 years old who had prediabetes (American Stroke Association, 2018; Kelly-Hayes, 2010; Yousufuddin & Young, 2019). A study by Bushnell et al reported that the risk of stroke doubles every 10 years after age 55 (Bushnell et al., 2014). The possible mechanism underlying the effect of age is that arteries naturally became narrower and harder with increasing age due to the change mediated by endothelial dysfunction and impaired cerebral autoregulation (Yousufuddin & Young, 2019). Moreover, certain stroke risk factors such as diabetes, hypertension, atrial fibrillation, and coronary and peripheral artery diseases steadily increase with age (Yousufuddin & Young, 2019). However, evidence also suggests that adolescents and younger people aged 15-49 years also have a high risk of stroke due to obesity and high blood pressure (Centers for Disease Control and Prevention, 2021b). In contrast to the previous findings, age was not significantly associated with stroke risks among persons with diabetes in this study (American Stroke Association, 2018; Kelly-Hayes, 2010; Yousufuddin & Young, 2019). The reason for this remains unclear. However, two or more comorbidities are quite common among older individuals with diabetes, which could potentially interact with conventional cardiovascular risk factors (i.e., age) to increase the risk of stroke (Yousufuddin & Young, 2019).

Similar to the findings of this study, several studies suggested that high blood cholesterol levels increased risk of stroke (Lisak et al., 2013; L. Sun et al., 2019).

Higher odds of stroke among individuals with both prediabetes and hypercholesterolemia could be explained by the changes of lipid metabolism among these populations. Adults with prediabetes have distinctive form of dyslipidemia characterized by low levels of High Density Lipoprotein (HDL)-cholesterol and moderately elevated levels of Triglyceride (TG)-rich lipoprotein (Garber, 2011). Dysmetabolism of TG-rich lipoprotein increases the level of smaller and denser Low Density Lipoprotein (LDL) particles. Overall, non-HDL cholesterol levels, including TG and LDL, almost always increase among adults with prediabetes. Moreover, increased non-HDL cholesterol levels due to lipid dysmetabolism and weakened blood vessels due to hyperglycemia among adults with prediabetes increase the risk of atherosclerosis and ischemic stroke (Menet et al., 2018). Surprisingly, hypercholesterolemia was not a significant predictor of stroke among adults with diabetes in this study. This is possibly due to the fact that anti-diabetic medications such as sulfonylurea and insulin can control hypercholesterolemia and, to some extent, reduce the risk of developing stroke (Abbate & Brunzell, 1990; Oki, 1995).

Risks of stroke among populations with diabetes vary by race. The higher odds of stroke among non-Hispanic Black compared to non-Hispanic White, identified in this study, is consistent with reports from previous studies (Gillum, 1999; Heyman et al., 1971; G. Howard et al., 1994; Kleindorfer, 2009). There is evidence that non-Hispanic Black populations have high risks of stroke because they are more likely to have hypertension and diabetes (Gillum, 1999; G. Howard et al., 1994; Kleindorfer, 2009). However, another study by Heyman et al suggested that even after adjusting for hypertension and diabetes, non-Hispanic Black individuals had consistently higher risk of stroke than non-Hispanic White (Heyman et al., 1971; V. J. Howard, 2013). Studies have reported that only half of the excess risk of stroke among non-Hispanic Black could be attributed to traditional risk factors (such as poor diet, obesity, and high salt diet), implying that genetic and biological factors might have potential roles in stroke disparities among non-Hispanic Black population (G. Howard et al., 2011; Kamin Mukaz et al., 2020; Safford et al., 2012). Additionally, non-Hispanic Black adults with diabetes often do not have access to healthcare due to low socioeconomic conditions and tend to have uncontrolled diabetes (Peek et al., 2007). The presence of inherent excess risk of stroke and uncontrolled diabetes may be responsible for higher odds of stroke among non-Hispanic Black individuals with diabetes compared to non-Hispanic White individuals with diabetes. Although Hispanics had seemingly higher odds of stroke than non-Hispanic White individuals, this association was not statistically significant. A study by Rodriguez et al also reported that age-adjusted prevalence of stroke among Hispanic individuals ≥18 years were similar to stroke prevalence among their non-Hispanic White counterparts (Rodriguez et al., 2014). However, this relationship may vary by geographic region as several studies, conducted in other US states, reported a significantly higher risk of stroke among Hispanic individuals compared to their non-Hispanic White counterparts. Similarly, the risk of stroke among non-Hispanic other races, including Asian and American Indian/Alaskan Native, also vary by geographic location (Trimble & Morgenstern, 2008). This study identified significantly lower risk of stroke among non-Hispanic other races than non-Hispanic White individuals in Florida, while studies in other US states reported the opposite (Day et al., 2006; Frey et al., 1998; Rosamond et al., 2008). However, it is worth pointing out that non-Hispanic other races represent a small portion of the Florida population. Overall, reasons for identified disparities in stroke risks among minority populations could be genetic and higher prevalence of traditional risk factors such as diabetes, hypertension, low socioeconomic status, and health care system challenges (Bolognini et al., 2009). Surprisingly, race was not a significant predictor of stroke among adults with prediabetes. The reason for this is not apparent but may be due to the fact that other factors such as age, hypertension, hypercholesterolemia are more important predictors of stroke among these populations.

Based on the findings from this study, adults that had both diabetes and depression had two times higher odds of stroke compared to those that had diabetes but no depression and this finding is consistent with those from a meta-analysis of 17 epidemiological prospective studies showing significant positive associations between depression and stroke even after adjusting for diabetes, hypertension, and other risk factors (Dong et al., 2012). Individuals experiencing depression tend to have unhealthy lifestyles, get less exercise, often times do smoke, and are more likely to miss prescribed medication (Mann, 2011). Other possible mechanisms linking depression to stroke could be inflammation, atherosclerosis, lesions in cerebral white matter, cardiac arrhythmia, and increased platelet activity (Dong et al., 2012; Mann, 2011).

4.5.1 Strengths and Limitations

To our knowledge, this is the first study that estimated the prevalence and investigated predictors of stroke among populations with prediabetes. The findings are critical for reducing stroke burden considering the fact that populations with prediabetes represent 1/3 of the US adult population. This is also the first study investigating predictors of stroke among populations with diabetes in Florida. Identifying populations that have prediabetes or diabetes with a high risk of stroke will help enhance evidence-based programs targeting those populations in Florida. These findings are important as the Florida Department of Health seeks to implement the new Paul Coverdell National Acute Stroke Program which aims to improve the quality of care for stroke patients. However, this study is not without limitations. The BRFSS survey did not gather information on types of stroke and so stroke risks could not be investigated based on types of stroke. This limitation notwithstanding, the findings of this study provide useful information to guide health planning and programs aimed at reducing stroke burden in Florida.

4.6 Conclusion

This study has shown evidence of higher prevalence of stroke among populations with prediabetes and diabetes than the general population in Florida. Study findings also provide some evidence that there may be differences in the importance of predictors of stroke among adults with prediabetes and those with diabetes. Regular checkups and controlling blood pressure and cholesterol levels among adults with prediabetes could help reduce stroke risks. On the other hand, non-Hispanic Black and Hispanic adults with diabetes are of specific concern as they have higher odds of stroke and represent almost half of the Florida population that have diabetes. Study findings will be useful in guiding health equity programs geared towards reducing stroke burden among populations with prediabetes and diabetes in Florida.

CHAPTER 5

Summary, Conclusions, and Recommendations

Diabetes is the seventh leading cause of death in the United States (US) (American Diabetes Association, 2020). Over the last 20 years, the number of diabetes patients in the US has doubled and is projected to double or triple again by 2050 (Centers for Disease Control and Prevention, 2010). Florida is one of the states of the diabetes belt, an area of the southeast US where diabetes prevalence was significantly higher than the rest of the country (Barker et al., 2011). The burden of diabetes has been increasing in Florida as evidenced by the fact that diabetes prevalence increased from 5.2% in 1995 to 12.6% in 2018, and diabetes-related ED visits increased by 54% between 2011 and 2016 (Florida Department of Health, 2022; Florida Diabetes Advisory Council, 2019). Florida spends $19.3 billion each year on prediabetes, diabetes, and diabetes-related complications (American Diabetes Association, 2016; Florida Department of Health, 2017). However, Florida is one of the states with the lowest DSME participation rate. Although geographic disparities in the burden of diabetes, DSME program availability, and diabetes-related ED visit risks were reported across the US (Barker et al., 2011; Lord et al., 2020; Paul et al., 2018; Ricci-Cabello et al., 2010; Rutledge et al., 2017; Shrestha, 2012; Walker et al., 2014, 2015), limited information is available on these disparities in Florida and yet this information is critical for guiding resource allocation targeted at reducing diabetes burden in Florida. The findings of the current study help to fill this gap and are useful in guiding evidence-based health planning in combating the diabetes problem. In addition, this study investigated the prevalence and predictors of stroke, one of the common diabetes-related complications, among adults with prediabetes or diabetes in Florida. This information is important for guiding health programs aimed at reducing stroke burden and improving the quality of life of populations with prediabetes and diabetes in Florida.

This study identified clusters of high diabetes prevalence and ED visit risks in northern and central Florida. The findings are consistent with those of a study by Barker *et al*., which reported that several counties of northern Florida had high diabetes prevalence due to geographical differences in the distribution of socio-cultural and genetic factors (Barker et al., 2011). Similar findings were reported in another study which identified several socio-economic determinants (high levels of poverty, percentage of non-Hispanic Black, obesity, and physical inactivity) as significant predictors of the reported hotspots of diabetes prevalence in northern Florida (Shrestha, 2012). This study also found that counties with high diabetes prevalence tended to have high diabetes-related ED visit risks even after adjusting for sociodemographic factors and healthcare access. This is because diabetes can affect many organ systems due to poor blood sugar control capacity resulting in hypo- or hyperglycemia. Hypoglycemia could lead to shock and death, while long-term hyperglycemia could be responsible for many complications such as neuropathy, nephropathy, retinopathy, stroke, cardiovascular, and peripheral vascular diseases (Deshpande et al., 2008) which may result in ED visit risks. Therefore, clusters of high ED visit risks identified in northern and central Florida could be due to high diabetes prevalence in those areas. Surprisingly, clusters of high DSME participation rates were observed in central Florida only. These findings further highlighted the importance of the diabetes problem in northern Florida, which had high diabetes prevalence and ED visit risks but low DSME participation.

Based on the findings from this study, counties with high percentages of rural residents are more likely to have low DSME participation rates. This might be due to lack of DSME program facilities in the rural counties of Florida. A study by Paul *et al*. reported that southeast regions of the US, including rural northern Florida, had high diabetes prevalence but few DSME centers (Paul et al., 2018). There is also evidence that rurality influences access to DSME more than socio-economic status such as poverty level (Graves et al., 2019). However, a New Jersey study reported that DSME participation in certain counties did not always reflect DSME program availability (Santorelli et al., 2017). Thus, DSME participation is affected by not only program availability but also by acceptability, accessibility, and other factors (Andersen, 1995; Graves, 2009). These findings implied that low DSME participation rates observed in rural areas of Florida could be the result of complex interactions between cultural, psychological, environmental, economic, and human resource factors such as transportation (Balamurugan et al., 2006; Rutledge et al., 2017), lack of specialists in rural areas, lack of diabetes educators (Powell et al., 2005), participants' literacy level, language barriers (Y.-H. Lee, 2020), lack of time, lack of childcare, participants' shame of illness, and participants lack of interest in their health (Testerman & Chase, 2018). Furthermore, lack of health insurance coverage among rural populations in Florida might have impacted utilization of DSME programs resulting in higher rates of complications and higher ED visit risks. This is consistent with the findings of this study which identified that counties with high percentages of populations with no health insurance coverage had high diabetes-related ED visit risks. Additionally, access to primary care for diabetes could be limited in rural areas due to the lack of health insurance coverage. Since diabetes is an ambulatory care sensitive condition, getting regular primary care could substantially reduce ED visit risks. Therefore, rural areas will need specific attention in order to address the issue of disparities in healthcare accessibility among diabetes patients in Florida.

The results of this study show that racial disparities play a significant role in geographic disparities of DSME participation and diabetes-related ED visit risks. Traditionally, Hispanics, Blacks, and Asians have low healthcare access compared to Whites with Hispanics facing the greatest barrier in the US (National Research Council, 2004). The findings of this study showed that DSME participation tended to be lower in the southern Florida counties that had higher proportion of Hispanic population but lower diabetes prevalence. There is evidence that Hispanics are less likely to participate in DSME due to financial constraints, work schedule conflicts, and lack of transportation (Francis et al., 2014; Hu et al., 2013; Whittemore, 2007). An individual-level study also identified language barrier as a significant predictor of low DSME participation among Hispanics (Martin et al., 2013; Testerman & Chase, 2018). This study identified significantly high ED visit risks in areas with high percentages of non-Hispanic Black population, which is consistent with findings of previous studies (Taylor et al., 2019; Uppal et al., 2022). A study by Uppal et al. reported that diabetes-specific ED use among non-Hispanic Black patients was approximately 3 times higher than among non-Hispanic White patients. This is because non-Hispanic Black patients have higher risks of diabetes-related complications such as albuminuria, retinopathy, lower extremity amputation, end-stage renal disease (ESRD), and worse glycemic control than their non-Hispanic White counterparts (Canedo et al., 2018; Osborn et al., 2013). Interestingly, this study showed that both non-Hispanic Black and Hispanic populations with diabetes had higher odds of stroke, which is one of the major diabetes-related complications. These findings have substantial policy implications in Florida. Non-Hispanic Black and Hispanic adults with diabetes represent almost half of the Florida population that have diabetes. Moreover, areas with high percentages of non-Hispanic Black had high diabetes-related ED visits, while areas with high percentages of Hispanic had low DSME participation rates in Florida. Therefore, implementing prevention programs targeted at these minority populations and ensuring equitable access to diabetes care could substantially reduce the burden of diabetes and diabetes-related complications in Florida.

There was evidence of a higher prevalence of stroke among populations with prediabetes and diabetes than the general population in Florida. However, there were differences in the importance of predictors of stroke among adults with prediabetes and those with diabetes. The odds of stroke were significantly ($p \leq 0.05$) higher among individuals with prediabetes that were ≥45 years old and had hypercholesterolemia. On the other hand, the odds of stroke among people with diabetes were significantly ($p \leq 0.05$) higher if they were non-Hispanic Black and had depression. However, hypertension was identified as a common predictor of stroke among adults with prediabetes or diabetes in this study, which is consistent with the findings from previous studies (American Heart Association, 2016; American Stroke Association, 2021c; Centers for Disease Control and Prevention, 2020e). Therefore, blood pressure control is an important intervention strategy to reduce stroke burden among both prediabetes and diabetes patients.

This is the first study that investigated the burden and predictors of stroke among populations with prediabetes and diabetes in Florida. These findings are important as the Florida Department of Health seeks to implement the Paul Coverdell National Acute Stroke Program which aims to improve the quality of care for stroke patients. In addition, this study confirmed geographic disparities and identified areas with high diabetes prevalence, DSME participation rates, and diabetes-related ED visit risks in Florida. The study has also demonstrated the usefulness of GIS and spatial epidemiologic/statistical approaches in investigating disparities in diabetes burden. These findings are useful for guiding public health efforts geared at reducing disparities and improving diabetes outcomes in Florida.

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