THE IMPACT OF SOCIAL DETERMINANTS OF HEALTH ON THE DIAGNOSIS OF TYPE 2 DIABETES MELLITUS AMONG ASIAN INDIANS IN NEW JERSEY

By

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ABSTRACT OF THE DISSERTATION

The Impact of Social Determinants of Health on the Diagnosis of Type 2 Diabetes Mellitus Among Asian Indians in New Jersey

by MAYA E JOSEPH

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Purpose: The purpose of this study was to examine the relationship between social determinants of health (SDH) and the diagnosis of type two diabetes mellitus (T2DM), and prediabetes (PDM) among Asian Indians (AI) in New Jersey (NJ).

Rationale: The global AI diaspora is experiencing disproportionately high rates of T2DM. Multiple studies in the US have indicated that AIs have a high prevalence of T2DM when compared to the other races after adjusting for confounding factors such as age and body mass index (BMI). Paradoxically, the prevalence of T2DM among AIs is not limited to the traditional risk factors of high BMI and waist circumferences.

Methods: The theoretical underpinning of this project is the Conceptual Framework of SDH by the Commission on Social Determinants of Health (CSDH) by the World Health Organization (WHO). This was a quantitative study with a cross-sectional study design. This study was a secondary data analysis using the NJ data from the Behavioral Risk Factor Surveillance System (BRFSS) of the Centers for Disease Control and Prevention (CDC) from 2013 to 2017. Non-institutionalized adults of 18 years and above participated in the study. Participants who were self-identified as AIs were included in the analyses. The independent variables of the study were income, education, employment, home ownership, internet use, BMI, exercise, fruit and vegetable intake, tobacco and alcohol consumption, and access to care factors such as health plan, medical check-ups, medical cost, and personal doctor. The dependent variables of this study were T2DM, PDM, and DS (diabetic status). Participants who were positive for either T2DM or PDM were categorized as positive for diabetic status (DS). Statistical analyses included descriptive statistics, chi-square analyses, logistic regression analyses, and mediation analyses.

Results: The results indicated that the odds of being diagnosed with T2DM were 68% lower with using the internet in comparison to not using the internet (OR = 0.32, 95% CI: 0.11-0.99) when adjusted for age, sex, BMI, and home ownership, and were 5 times higher with having a personal doctor than with not having a personal doctor (OR =5.34, 95% CI: 1.84-15.50). The logistic regression analysis did not identify statistically significant structural social determinants for the diagnosis of PDM. The odds of being diagnosed with PDM were 11 times higher among AIs who reported having at least one medical check-up in the last two years than those who reported having no medical check-ups in the last two years (OR =10.92, 95% CI: 1.27-94).

The odds of having a positive DS were 66% lower with the use of the internet (OR =0.34, 95% CI: 0.14-0.84) when adjusted for age, sex, BMI, and homeownership compared to not using the internet. The odds of having a positive DS were 4 times higher for AIs who reported having medical checkups in the last two years (OR = 4.40, 95% CI: 1.05-18.48) than those who did not have medical check-ups in the last two years and 4 times higher for those who have a personal doctor (OR = 4.03, 95% CI: 2.03-8.00) than those who did not have a personal doctor.

Moreover, the odds of being diagnosed with T2DM were 4 times higher among AIs greater than 45 years of age in comparison to AIs less than 45 years (OR = 3.89, 95% CI: 1.78-8.52), and the odds of having a positive DS were 4 times higher among AIs older than 45 years (OR = 3.89, 95% CI: 1.78-8.52). There was no statistically significant relationship between behavioral factors and T2DM, PDM, or DS in this study. Mediation analysis showed that 14% of the variation in the relationship between internet use and diagnosis of T2DM was explained by having a personal doctor and 8% of the variation in the relationship between internet use and diagnosis of DS was explained by having a personal doctor. One percent of the variance in the relationship between age and diagnosis of PDM was explained by the mediator medical check-up. As additional findings, there was a high proportion of high BMI (69.2%) among AIs in this study. The internet use was higher among participants of younger age and higher income.

Conclusions: There is substantial evidence in the literature about the relationship of Socioeconomic Position(SEP) and behavioral factors with the diagnosis of T2DM. However, there is a lack of consistency in the relationships and dearth of studies on this topic among AIs in NJ. This study indicates a significant relationship between internet use, having personal doctor, and the diagnosis of DS among AIs in NJ. While healthier behaviors and BMI are associated with a lower diagnosis of DS in the general population, this study among AIs did not show any significant association between healthier behaviors and BMI and the diagnosis of DS. The nature of the relationships established in this study should be explored further using studies with a larger sample size, survey tools specifically developed for AIs, and using longitudinal study designs. The results of this study have implications on public health, clinical, and research aspects of health care.

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DEDICATION

I dedicate this work to my family. My parents for their unfailing confidence in me, my in-laws who helped to fill my role in the family during these tough years of work and study, and my sister who is always the happiest person about my accomplishments. Finally, I want to dedicate this work to both my sweet kids who are excited to have mom's challenging project complete, and to my husband who stood strong by my side with his endless love, patience, and care.

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CHAPTER 1: THE PROBLEM

The unprecedented growth of type 2 Diabetes Mellitus (T2DM) in the Asian Indian (AI) immigrant population in the US is a growing health hazard (CDC, 2019; Kanaya et al., 2014; O'Keefe, DiNicolantonio, Patil, Helzberg, & Lavie, 2016). Elevated body mass index (BMI) and waist circumference are considered the most common risk factors for T2DM. Yet paradoxically, AIs are known to develop T2DM even at lower BMI and waist circumferences (Venkat Narayan et al., 2019). Multiple studies have reported that immigrants from the Indian subcontinent had the highest age-adjusted T2DM prevalence compared to all other immigrants in the US (Commodore-Mensah et al., 2018; Lee et al., 2011; Venkat Narayan et al., 2019). The highest odds of diabetes prevalence were also noted in AIs compared to all other Asian American, White, Hispanic, and Black participants after adjusting for age, sex, BMI, education, income, smoking, alcohol use, and physical activity (Lee et al., 2011). Another study reported that South Asians, the majority of whom are AIs, had the highest age-adjusted prevalence of diabetes (23%) compared to White (6%), Black (18%), Latino (17%), and Chinese (13%) participants (Kanaya et al., 2014). In addition to these studies, national health surveys provide a good representation of this minority population.

A cross-sectional analysis of the 2010-2016 National Health Interview Survey (NHIS) indicated that the immigrants from the Indian subcontinent had a strikingly high prevalence for both T2DM (16.3%) and overweight/obesity (80.4%) (Commodore-Mensah et al., 2018). The American Diabetes Association indicates that nearly 263,000 (11.2 %) of AIs in the US have T2DM and 860,000 (36%) have prediabetes (American Diabetes Association, 2017).

The notion of racial/ethnic disparities in T2DM prevalence among AIs is evident in the literature. Asian Indians are typically diagnosed with T2DM a decade earlier than other ethnicities, leading to more complications and early death in this ethnic group (Amutha et al., 2011; Shah & Mohan, 2015). Rapid conversion of normoglycemia to dysglycemia is also noted in AIs (Anjana et al., 2015). With the earlier onset of T2DM, complications are more likely to occur at middle age, significantly reducing the quality of life, increasing health care spending, and decreasing the productivity of those affected (Amutha et al., 2011). Moreover, T2DM is a well-established risk factor for increased morbidity and mortality from cardiovascular diseases (Martin-Timon et al., 2014), particularly atherosclerosis and hypertension, which increase the risk for stroke, myocardial infarction, and multiorgan damage.

The genetic predisposition of T2DM among AIs is multifactorial. Features of the AI phenotype include an early decline in beta-cell function, higher insulin resistance, and higher body fat composition with lesser muscle mass than the other racial/ethnic groups (Bhardwaj & Misra, 2015). Other factors associated with the high genetic susceptibility of AIs for T2DM include the thrifty genotype hypothesis, and genetic polymorphism (Rubina Tabassum et al., 2013; Southam et al., 2009). Meanwhile, a near ten-fold increase in the incidence of T2DM among AIs just in the last two decades cannot be explained by genetic factors alone, since the genetic transformation is a gradual process. This emphasizes the need to explore the impact of social and environmental factors on the diagnosis of T2DM in this population.

Asian Indians are a uniquely heterogeneous population, exhibiting extreme diversity in culture, religious beliefs, socio-economic position (SEP), education, and occupation. After migration to the US, AIs are often exposed to an environmental transformation that significantly affects their SEP and material circumstances (Tiagi, 2013). Thus, social, and environmental factors, frequently referred to as 'social determinants of health'(SDH) become highly relevant in the discussion of the increasing prevalence of T2DM among AIs diaspora living in the US. Nonetheless, little is known about the impact of SDH on the prevalence of T2DM in this specific minority group.

Asian Indians are the second-largest group of foreign-born immigrants in the US, totaling about 2.4 million in 2015. Moreover, AIs are the fastest-growing immigrant population in the US, as evidenced by an eleven-fold increase in the number of AIs in the US from 1980 to 2010. According to the Migration Policy Institute, the number of AI Immigrants in the United States is roughly doubling every decade and a large number of Asian Indians live in the tristate area including New Jersey (Pew Charitable Trusts, 2014). Thus, it is important for US health care providers to be aware of the growing prevalence of T2DM as well as contributing factors to T2DM in AIs and to be informed about the specific needs of this population (American Diabetes Association, 2018a) to effectively care for them. Health care personnel including nurses are required to provide culturally competent care. Understanding the role of SDH in the prevalence of T2DM among AI immigrants will assist health care providers to make informed decisions while caring for this population. This awareness will also help nurses to play a key role in developing population-specific prevention programs for T2DM in AIs in the US and other developed countries.

The financial implications of T2DM in America are incredibly important. The total cost of diagnosed diabetes in the US is $327 billion (American Diabetes

Association, 2018a). As of 2016, total health care spending in the US has reached $ 3.3 trillion, 75% of which is attributed to the cost of chronic diseases, including T2DM. It is also important to note that the treatment costs are small (21%) compared to productivity losses (79%). A large proportion of AIs in the US is 19-64 years of age, which represents the working population of the country (Batalova & Zong, 2017). This enormous social and personal financial burden makes a compelling case for T2DM prevention among AIs in the US.

Social Determinants of Health

Social determinants of health can be classified as structural and intermediary determinants, as shown in Figure 1 (Solar & Irwin, 2010). Structural SDH includes factors such as income, education, occupation, home ownership, and internet use which determine the SEP of the individual. These SEP factors influence exposure to health-promoting and health-damaging conditions and the availability of appropriate health care. On the other hand, intermediary determinants include behavioral factors, access to health care factors, and biological factors that are affected by the SEP of the person. Demographical factors age, sex, and marital status were not considered under SDH since they are not influenced by the social factors.

Figure 1. The Sequence of Structural and Intermediary Determinants

In this study, the independent variables were SEP variables and intermediary variables such as exercise, fruit and vegetable intake, tobacco and alcohol consumption, and access to care factors such as health plan, medical check-ups, medical cost, and personal doctor. In addition, the independent variables also included the biological factor BMI which is affected by social factors. The dependent variables of this study were T2DM, prediabetes (PDM), and diabetes status (DS). Diabetes status is the presence of either T2DM or PDM diagnosis.

Previous studies have indicated that low physical activity, high prevalence of metabolic syndrome among AIs, and diabetogenic dietary patterns are major risk factors for the high prevalence of T2DM among AIs in their home country as well as in the US (Daniel et al., 2013; Mukherjea et al., 2013; Shah & Mohan, 2015). However, studies among AIs in the US are limited in number and quality. There is a dearth of studies that addressed the impact of many SDH on the high prevalence of T2DM in this minority immigrant population in the United States. An effective model for targeted T2DM prevention and management for Asian Indian immigrants in the United States is currently lacking. Increased awareness of additional social determinant factors is also needed to guide the development of a culturally tailored and sustainable model for T2DM prevention for the AI population in the US.

Study Purpose and Research Questions

The purpose of this study was to explore the relationship between structural social determinants, intermediary determinants, and the diagnosis of diabetes status in AIs in the state of New Jersey. The study addressed the following research questions:

1. Is there a relationship between SEP (education/ occupation/ income/ homeownership/ internet) and diagnosis of DS among AIs in NJ?

2. Is there a relationship between health-related behaviors (fruit and vegetable intake, consumption of tobacco or alcohol, and exercise) and the diagnosis of DS in AIs in NJ?
3. Is there a relationship between access to care factors (health plan, medical check-ups, medical cost, and personal doctor) and the diagnosis of DS among AIs in NJ?
4. Is there a relationship between SEP (education/ occupation/income/ homeownership/ internet) and health-related behaviors (fruit and vegetable intake, consumption of tobacco or alcohol, and exercise) among AIs in NJ?
5. Is there a relationship between SEP (education/ occupation/income/ homeownership/ internet) and access to care factors (health plan, medical check-ups, medical cost, and personal doctor) among AIs in NJ?
6. Do intermediary determinants (behavioral determinants, and access to care factors) mediate the relationship between SEP and the diagnosis of DS among AIs in the NJ?

Definition of Terms

Type 2 Diabetes Mellitus (T2DM) is a progressive metabolic disorder resulting from the combination of resistance to insulin action, inadequate insulin secretion, and excessive or inappropriate glucagon secretion resulting in hyperglycemia and associated dysfunctions (Khardori, 2019). In contrast, T1DM is the condition where the body does not produce enough insulin which keeps blood sugar at normal levels. Prediabetes (PDM) occurs when the blood sugar levels are higher than normal, however, not high enough for the individual to be diagnosed as diabetic (American Diabetes Association, 2021). Diabetes status in this study refers to the diagnosis of either T2DM or PDM.

Theoretical Framework

The World Health Organization (WHO) defines the social determinants of health as the conditions in which people are born, grow, live, work, and age (World Health Organization, 2008). The structural SDH are the factors that construct social classes and determine the individual's rank among the social classes. These include SEP, which refers to the status of the societal hierarchical structure concerning access to care, goods, and knowledge. The SEP is also connected to income, occupation, and education. Intermediary determinants are the factors resulting from social stratification, which regulates the differences in exposure to conditions that affect health. Intermediary determinants include material circumstances such as health-promoting or health-damaging behaviors, health system, and psychosocial factors such as stressful living conditions.

The independent variables in this study were selected structural and intermediary determinants, and the dependent variables are the diagnosis of T2DM and prediabetes. The intermediary determinants of health and access to health care factors were analyzed for mediation. The operational definitions of the variables were participant responses on the BRFSS items that related to each study variable, as described in greater detail in the methods chapter.

Significance of the Study

The findings of this study will contribute to the development of effective culturally tailored strategies to address the social determinants factors that impact the diagnosis of DS among AIs. Awareness about these social determinant factors will be important when considering proper screening strategies, patient education, and policy development for the AI population. This study's results will be useful in preventing the inequities in diabetes-related health care among members of the AI minority in NJ.

CHAPTER 2: REVIEW OF THE LITERATURE

A non-traditional dissertation format has been used for this dissertation. Rutgers Graduate School-Newark accepts dissertation formats with data chapters written in a manuscript form ready for submission to peer-reviewed journals. In this case, Chapter 1 and Chapters 3 -6 are written in the traditional dissertation format. Separated in a manuscript format, Chapter 2 reports a review of the literature on the impact of social determinants of health on the prevalence of type 2 diabetes mellitus among Asian Indians in the NJ, with the references. An evidence table of the studies that were included in the literature review is provided in Appendix 1.

Abstract

The global Asian Indian (AI) diaspora is experiencing disproportionately high rates of Type 2 diabetes mellitus (T2DM). Multiple studies in the US have indicated that AIs have the highest prevalence of T2DM when compared to the other ethnicities (Commodore-Mensah et al., 2018; Kanaya et al., 2014; Lee et al., 2011; Venkataraman et al., 2004) after adjusting for confounding factors such as age. As per the American Diabetes Association, about 263,000 (11.2 %) of AIs in the US have T2DM, and 860,000 (36%) of AIs have prediabetes, percentages inexplicably higher than other ethnic groups (American Diabetes Association, 2017). Paradoxically, the prevalence of T2DM among AIs is not limited to the traditional risk factors of high body mass index (BMI) and waist circumferences (O'Keefe, DiNicolantonio, Patil, Helzberg, Lavie, et al., 2016). This review aims to explore the relationship of social determinants of health (SDH) on the prevalence of T2DM among AIs in the US. The theoretical underpinning of this review is

the Conceptual Framework of SDH by the Commission on Social Determinants of Health (CSDH) by WHO (Solar & Irwin, 2010).

Key Words

Social determinants of health, behavioral factors, diabetes, socioeconomic status, Asian Indians, Diet, Physical activity**.**

Introduction

The unprecedented growth of Type 2 diabetes mellitus (T2DM) among the Asian Indian (AI) population in the US is a growing health hazard that has been understudied. While high body mass index (BMI) and waist circumference are considered common risk factors for T2DM, evidence suggests that AIs are at high risk for T2DM at a lower BMI and waist circumferences, compared to other ethnicities (O'Keefe, DiNicolantonio, Patil, Helzberg, Lavie, et al., 2016). The traditional risk factor of larger BMI further increases the risk of T2DM in this population. AIs are diagnosed with T2DM a decade earlier compared to any other ethnic group, leading to severe complications and early death in this population (Misra et al., 2014). At the same time, AIs are an extremely heterogeneous group about religion, cultural beliefs, education, socioeconomic status, and languages. Immigration to the US has brought forth significant changes in the socio-economic environment in this minority group. Thus, social and environmental factors might be affecting the high prevalence of T2DM among AIs in the US. Currently, there is a paucity of research describing the relationship between SDH and the risk for T2DM among AIs in the US. Strategies to prevent or delay the onset of T2DM in this population will only be effective if these relationships are established using robust methods.

Significance

T2DM is a global health threat. Close to 30 million people in the US (over 9% of the total US population) have been diagnosed with T2DM, and that number is expected to grow to nearly 55 million in the next decade (American Diabetes Association, 2018b). As a chronic, progressive disease, the profound physical, emotional and economic effects of T2DM extend beyond the affected individual to the family, community, and society (Rowley et al., 2017). Several national and international T2DM prevention programs have been developed to address this widespread health care issue. The need for culturally tailored strategies to ensure the effectiveness of these programs is emphasized in the literature (Joo, 2014).

AIs are the second largest group of foreign-born immigrants in the US, numbering about 2.4 million individuals. There was an eleven-fold increase in the number of AIs who migrated to the US from 1980 to 2010 (Batalova & Zong, 2017). According to the Migration Policy Institute, the number of AI immigrants in the US is roughly doubling every decade. As per CDC's diabetes fact sheets and national data, about 263,000 (11.2 %) of AIs have T2DM, and 860,000 (36%) of AIs have prediabetes (American Diabetes Association, 2017). In the context of the high T2DM prevalence in the US, numerous studies indicate AIs in the US have the highest odds of T2DM prevalence when compared to all Asian Americans, Whites, Hispanics, and Blacks (Commodore-Mensah et al., 2018; Kanaya et al., 2014; Lee et al., 2011; Venkataraman et al., 2004) . This high prevalence of T2DM among AIs is after adjusting for age, sex, BMI, education, income, smoking, alcohol use, and physical activity (Lee et al., 2011). Nonetheless, no effective prevention strategy has been shown to meet the needs of AIs in the US.

Despite the disproportionately high prevalence, T2DM has an atypical presentation among AIs. A high BMI and larger waist circumferences are generally considered the most common risk factors of T2DM. Paradoxically, AIs are known to develop T2DM at a low BMI and smaller waist circumference. AIs are also likely to be diagnosed with T2DM a decade earlier than other ethnic groups, leading to more complications and early deaths in this population (Amutha et al., 2011; Shah & Mohan, 2015). Recent studies also indicate poor outcomes with SARS-CoV-2 infection among AIs with diabetes. SARS-CoV-2 infection also causes T2DM among AIs same as in other populations (Shivane et al., 2020). These factors are to be brought to the attention of health care providers to attend to the needs of the AI minority in the US.

Meanwhile, there has been a ten-fold increase in the prevalence of T2DM among AIs just in the last two decades; this increase cannot be explained by genetic factors alone (Shah & Mohan, 2015). This dramatic increase in the prevalence of T2DM points to the significance of possible involvement of social and environmental factors since the change in genetic factors is a gradual and slow process (Shah & Mohan, 2015). AIs are a uniquely heterogeneous population with extreme diversity in culture, religion, socio-economic status, and heterogeneity in the prevalence of T2DM (Joshi, 2012). There are several religions represented in India, each of which is unique in culture, rituals, and rites. AIs speak more than two hundred languages and more than a thousand dialects. The dietary patterns of people from northern and southern India differ significantly. Their customs and manners are also diverse. Thus, these social and environmental factors, also termed as ‘social determinants of health’ (SDH), are defined as the living conditions of individuals along with the bigger context of social, cultural, and political forces and systems that create these conditions (World Health Organization, 2008), are likely to be highly relevant in the high prevalence of T2DM among AIs living in the US.

Information about the specific needs of this population is imperative to adequately care for AIs in the US. Moreover, a thorough understanding of the role of SDH in the context of the growing prevalence of T2DM among AIs will help health care practitioners to make informed decisions about caring for this population and to develop targeted prevention programs for T2DM in AIs in the US.

The health care costs for T2DM in the US are also incredibly high. The total estimated direct and indirect costs of diagnosed T2DM in the US are $327 billion/year (American Diabetes Association, 2017). With chronic illnesses such as T2DM, treatment costs are small (21%) compared to productivity losses (79%). Since the majority of AIs in the US are of working age (19-64 years of age) (Batalova & Zong, 2017), T2DM can cause a significant financial burden for AIs, their families, and society. This enormous social, personal, and financial burden makes a compelling case for further exploration of factors affecting T2DM among AIs in the US. Interestingly, little is known about the impact of SDH on the prevalence of T2DM in this specific minority group. Therefore, understanding the relationships between SDH and T2DM among AIs is essential to identify the gaps in the literature.

Theoretical/Conceptual Framework

A conceptual framework for action on the SDH by the Commission of Social Determinants of Health (CSDH) of the World Health Organization (WHO) (Solar & Irwin, 2010) is the theory of interest of this paper. The CSDH framework is based on the premise that health care behaviors, psychosocial stressors, and material resources can be a product of social structure and socioeconomic position, rather than individual responsibility. The CSDH framework of SDH includes multiple elements named structural and intermediary SDH, and their impact on equity in health and wellbeing (Solar & Irwin, 2010).

According to the CSDH framework, structural SDH such as social, economic, and political mechanisms generate different socioeconomic positions (SEP) depending on the factors including income, occupation, and education (Solar & Irwin, 2010). SEP governs intermediary SDH, which, along with social cohesion, causes differences in exposure and vulnerability to health-related conditions (Solar & Irwin, 2010). Illness has feedback on SEP due to its effect on employment. Some epidemics also generate feedback to affect the functioning of socio-economic and political contexts (Solar & Irwin, 2010). The magnitude of disease can affect the life expectancy and productivity of the people leading to significant changes in social systems by their impact on political and economic situations. The HIV/AIDS pandemic in Africa is an example. The CSDH framework is provided in Figure 1.

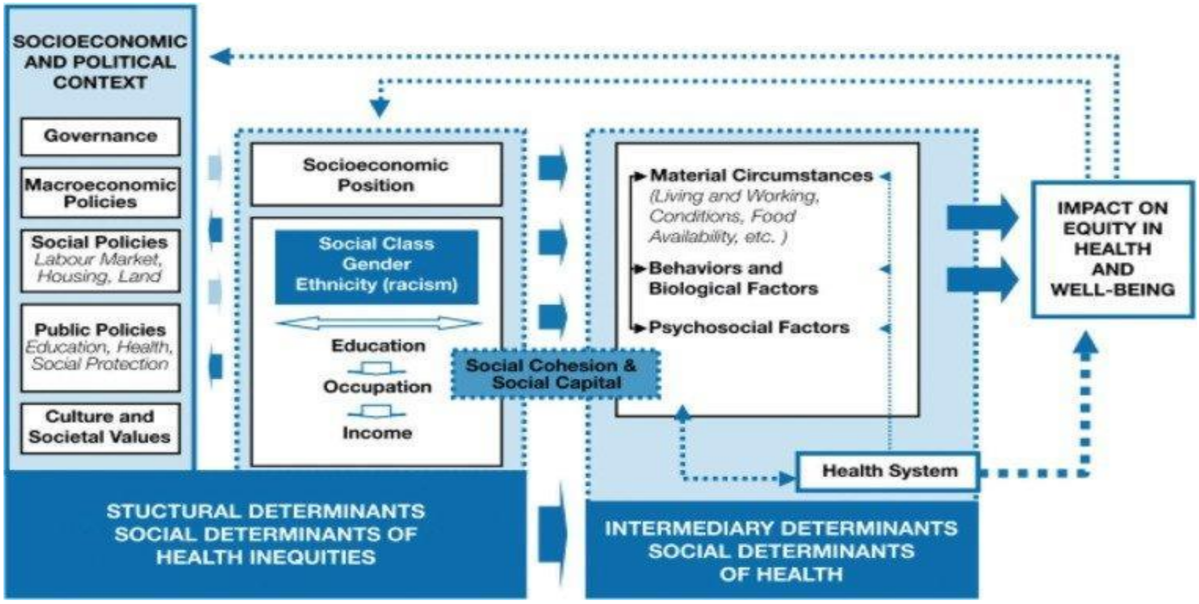


Figure 2. Reprinted from Commission on Social Determinants of Health Framework adapted from A Conceptual Framework for Action on the Social Determinants of Health, Paper 2, O. Solar & A. Irwin, Final form of the conceptual framework, Page 48., WHO (2010), http://apps.who.int/iris/bitstream/handle/10665/44489/9789241500852_eng.pdf, accessed on 12.12.2018.

The Commission on Social Determinants of Health (CSDH) framework of the WHO offers a structure to understand better both the SDH and the relationships associated with the problem. The CSDH framework divides the SDH into two domains, structural, and intermediary SDH. *Structural SDH* includes education, occupation, income, and marital status, which determines the social class, and thereby, the SEP of the individual (Solar & Irwin, 2010). The SEP then influences exposure to healthy and unhealthy living conditions and the availability of appropriate health care. For example, people from high SEP can afford gym memberships and continue to exercise even in winter weather conditions. *Intermediary determinant* refers to material circumstances, behavioral factors, biological factors, and psychosocial factors that result from the socioeconomic position of the person (Solar & Irwin, 2010). Intermediary SDH includes factors such as housing, physical inactivity, dietary habits, psychological stress, tobacco/alcohol use, availability of insurance, and health care access. Exposure to intermediary SDH factors can prevent or promote disease conditions. For example, regular exercise can help prevent or delay the onset of T2DM. Thus, the CSDH framework explains that the structural SDH leads to the differences in an individual's differential exposure to the intermediary SDH, which further causes alterations in health and wellbeing (Solar & Irwin, 2010).

Structural and intermediary SDH are instrumental in designing appropriate interventions to achieve the desired health outcomes. The objective of this review is to examine the relationships of structural SDH (socioeconomic position including income, occupation, education, marital status) and the intermediary SDH (intake of sugar-sweetened beverages, fruits and vegetable intake, use of tobacco, alcohol consumption, exercise, emotional stress, and health care coverage) with the prevalence of T2DM among AIs. Table 1 refers to the SDH included in this review.

The review will be divided into three domains based on the relationships explained in the CSDH framework. The first domain of the review will analyze the studies that examined the relationships between structural SDH and the prevalence of T2DM among AIs. The main structural SDH discussed in the studies reviewed are family income and education level. The second domain will review the studies that examined the relationships between structural and intermediary SDH. The third domain of the review will include those studies that examine the relationship between intermediary SDH and the prevalence of T2DM among AIs.

Literature Review Strategy

A thorough literature search was conducted to collect empirical evidence regarding T2DM among AIs. Ovid MEDLINE, PubMed, CINAHL, SCOPUS, and Psych info databases were searched for relevant literature published between 2000 and 2019. The keywords used for the search included social determinants of health, behavioral factors, diabetes, socioeconomic status, Asian Indians, diet, physical activity, health care access, and emotional support. Although the initial search was intended to target studies conducted in the US, due to the dearth of studies about AIs, the search was expanded to include the other countries with Indian immigrants and also India, where most of the studies were conducted. A snowballing approach was also used to obtain relevant articles. A search for gray literature included conference papers and policy reviews. A comprehensive review of the resulting 21 studies was then conducted to analyze the relationships between SDH and T2DM prevalence among AIs in the US.

Literature Review Results

This search initially yielded 519 articles. Duplicates were removed and the abstracts of the remaining 363 articles were screened further. Studies about the management of T2DM, studies conducted in other populations, and reviews were removed during the abstract review. A detailed abstract review resulted in 21 relevant studies. Out of 21 primary studies, 18 of them were quantitative studies, and three were qualitative studies.

Structural SDH and Prevalence of T2DM

All eleven studies that examined the relationships between structural SDH and the prevalence of T2DM were cross-sectional studies, and two of them were secondary data analyses. The theoretical concept of socioeconomic position was operationalized as educational level or family income level. Three out of eleven studies were conducted in the US.

Upon review, there is a lack of consistency in the relationships established between socioeconomic position (SEP) and the T2DM prevalence among AIs in the US. While four studies indicated that high SEP was positively related to the prevalence of T2DM (Agrawal & Ebrahim, 2012; Boddula et al., 2008; Gujral et al., 2015; Gupta et al., 2012), one study indicated a curvilinear relationship between SEP and the prevalence of T2DM (Nguyen et al., 2014). The curvilinear relationship refers to the finding that increasing income levels in the low to mid-SEP was associated with an increase in the prevalence of T2DM and increasing income levels in the high SEP was related to a decreased prevalence of T2DM among AIs in the US.

Gujral et al., (2016) conducted a comparison study comparing AIs in the US and India and indicated that including education and height as a proxy for SEP, SEP was more associated with the prevalence of T2DM than the place of residence (Gujral et al., 2016). Misra et al. (2018) indicated that higher income was linked to a higher risk for T2DM (A. Misra et al., 2018). This study included participants from seven cities in the US, which increases the representation of the sample. Meanwhile, studies by Gupta et al. and Kanaya et al. concluded that there is no association between SEP and the prevalence of T2DM among AIs (Gupta et al., 2012; Kanaya et al., 2010). The study by Gupta et al. was conducted in India. Srivastava and Ghorpade (2014) in their study in India noted that low income, higher education, and unemployment were related to an increased risk for T2DM (Shrivastava & Ghorpade, 2014). Venkatesh et al. (2017) in their study indicated that dietary acculturation, a component of structural SDH, was associated with an increased prevalence of T2DM (Venkatesh et al., 2017). Joseph et al. (2018) mentioned the mediating role of acculturation and lifestyle factors in increasing the risk for diabetes (Joseph et al., 2018). Conflicting findings point to the need for more research in this area.

Structural SDH and Intermediary Determinants

A total of nine studies examined the relationships between structural and intermediary SDH among AIs. Three of these studies were conducted in the US, one was carried out in the UK and the others in India. The authors of three out of nine studies indicated that fruit and vegetable consumption, as well as compliance with medical examinations, were directly related to high-income levels (Denis Anthony et al., 2012; Gupta et al., 2012; Mehrotra et al., 2012). Nguyen, Moser, and Chou in their study in the US noted curvilinear trends in the relationship between SEP and health-related behaviors. A curvilinear trend referred to an increase in unhealthy behaviors from low to mid-SEP and returning to healthier behaviors in higher SEP. Unhealthy conditions such as smoking/tobacco use, low physical activity, psychosocial stress, and depression were higher in the low and middle socioeconomic groups compared to participants from the high SEP (Nguyen et al., 2014). On the contrary, behaviors such as alcohol and fat intake were higher in high SEP groups (Gupta et al., 2012).

In the study conducted in San Francisco, Gadgil et al. noted no significant relationships between income or level of education and dietary intake pattern (Gadgil et al., 2014). However, it is essential to note that this study was a pilot study (N = 150), conducted among a socioeconomically advantaged group. On the other hand, the authors of both qualitative studies noted that cultural and social aspects influence unhealthy dietary behaviors among AI participants (Fleming et al., 2008; Mukherjea et al., 2013). Similarly, Fleming (2008) in an observational study indicated the strong connection between culture and compliance with a healthy diet among AIs. Nativity i.e. the country in which the participant was born also impacts the health behaviors and perspectives of AIs (Dhar et al., 2019).

Intermediary Determinants and Prevalence of T2DM

The authors of the reviewed studies indicated that intermediary SDH such as low physical activity, high prevalence of metabolic syndrome, and dietary patterns such as high carbohydrate intake, was linked to the high prevalence of T2DM among AIs in the US (Aravindalochanan et al., 2014; Ghai et al., 2012; Kanaya et al., 2014; A. Misra et al., 2018; Mukherjea et al., 2013; Mukherjee et al., 2009; Ram et al., 2014; Ram et al., 2006). A higher fruit and vegetable consumption and vegetarian status were linked to a lower risk for T2DM. On the other hand, three studies indicated that lower fruit and vegetable intake was related to lower T2DM prevalence among AIs in the US. These findings were after controlling for demographic, lifestyle, and clinical factors (Ghai et al., 2012; A. Misra et al., 2018; Ram et al., 2014). Fruits and vegetable consumption for urban adult AIs were far below recommendations (Radhika et al., 2011; Ye et al., 2009). Ram et al. (2006) also added that reductions in portion size, BMI, and fat and carbohydrate consumption were related to reduced risk of T2DM among AIs in India, independent of physical activity (Ram et al., 2006).

On the contrary, Kanaya et al. (2010) noted that lower carbohydrate intake and higher protein intake were linked to more T2DM prevalence among AIs in the US (Kanaya et al., 2010). This could be reverse causation since the study was a cross-sectional study. The study in the US was a cross-sectional study with a sample size of 150, while the Ram et al. study was an experimental study with a sample size of 517. The location of the study, the lifestyle differences in both countries, and other pertinent sociocultural influences could also be the basis for these conflicting findings. Another finding was that daily fish consumption was linked to increased odds of T2DM among AIs by 2 times after adjusting for dietary, lifestyle, socioeconomic, and demographic factors (odds ratio [OR]: 2.02; 95% confidence interval [CI], 1.59–2.57; $p < .001$). The unadjusted physical inactivity was highest among AIs than other ethnic populations in the US and was still higher than Whites when it was adjusted for covariates (Ye et al., 2009). AIs in this study were 2.3 times more likely to have diabetes as well.

Age, BMI, and emotional stress are considered intermediary SDH. A ten-year longitudinal study conducted in South India indicated that age > 45 years, family history of T2DM, BMI ≥ 25 kg/m, and presence of central obesity were the highest contributing risk factors for T2DM (Dhar et al., 2019; Fitzgerald et al., 2020; Nagarathna et al., 2020; Venkataraman et al., 2004; Vijayakumar et al., 2019). Higher age was associated with a higher incidence of T2DM among AIs (Shrivastava & Ghorpade, 2014). Paradoxically, a cohort study in rural India noted that close to one-third (31.7%) of T2DM incidence occurred at ages younger than 40 years (Ghorpade et al., 2013). Even though AIs tend to develop T2DM with a normal BMI, an increase in BMI was related to an increased risk for T2DM (He et al., 2015). The mean waist-weight ratio was higher ($p < 0.001$) in AIs (men 1.35 ± 0.002, and women 1.45 ± 0.002) than in all the US groups (Bajaj et al., 2014; Fitzgerald et al., 2020). However, it is essential to note that the 56.4% increase in T2DM that occurred from 1989-2000 was with no change in BMI and also with no gender differences (Ramachandran et al., 2002). Interestingly, no studies were found addressing the association between emotional stress and T2DM prevalence among AIs in the US.

Gaps in the Literature

There is a dearth of studies that address the impact of many of the SDH on the prevalence of T2DM among the AI population in the US. This comprehensive review of literature that focused on the structural SDH, intermediary SDH, and prevalence of T2DM among AIs in the US suggests that these relationships are not consistent throughout the literature. However, none of these studies primarily addressed the impact of SDH on the T2DM prevalence among AIs in the US. Barely any studies included factors such as emotional stress or access to care and their relationship to T2DM prevalence.

The studies conducted about the prevalence of T2DM among AIs in the US are mostly cross-sectional studies, which cannot adequately demonstrate causality. Moreover, since the location of most of the studies in the US was California, the results may not be generalizable to AIs living in other parts of the US. Studies outside the US can have many contextual variables which further restrict the generalization of the study findings to all AIs in the US. Moreover, AIs are a highly heterogeneous population. Altogether there is a demand for more research addressing the unique nature of several AI subgroups.

Some studies included a convenience sampling method rather than random sampling (Daniel et al., 2013; Gadgil et al., 2015; Gupta et al., 2012; Mehrotra et al., 2012), which can affect the external validity of these studies. Moreover, a few studies had small sample sizes, which negatively influenced the power of the study (Fleming et al., 2008; Gadgil et al., 2015; Mukherjea et al., 2013). Alternatively, such conflicting findings may be due to the heterogeneity of AI immigrant groups.

The absence of an adequate number of longitudinal studies supporting causation is yet another gap in the literature. Only longitudinal studies can verify the reverse causation in the relationships. Therefore, recommendations for future studies include conducting longitudinal studies to obtain more information on the feedback mechanisms in the system. Since the location of most US studies was California, future study samples should be drawn from other states with large numbers of AI immigrants. Improving the sample representativeness will increase the external validity of the study. Random sampling should be considered in future studies to increase the internal validity of the study findings.

Likewise, secondary analyses of available data sets with weighted averages will provide valuable information about this population. Weighted samples from different religions, areas of Indian origin, gender, age group are all needed to address the heterogeneity of AI immigrants in future studies adequately. Since there is a paucity of qualitative studies addressing the relationship between SDH and T2DM in this population, more qualitative studies are needed to understand the phenomenon better. Studies should also address other variables such as acculturation and generation status which can significantly affect health care behaviors and act as a confounding variable in the relationship between SDH and prevalence of T2DM. In conclusion, more empirical research is needed to understand specifics about T2DM in AIs.

Conclusions

This review of literature has supported the belief that structural SDH may be linked to the individual's exposure to intermediary SDH, which in turn can have a positive or negative relationship with the prevalence of T2DM. Income, occupation, education were the components of SEP that were used to operationalize the theoretical construct of structural SDH in the reviewed studies. The components of intermediary SDH included health-related behaviors, health care access, and psychosocial stress. Many SDH components still require analysis in the context of high T2DM prevalence among Asian Indians in the United States.

A positive relationship between SEP and the prevalence of T2DM was prominent in the studies that analyzed structural SDH and the prevalence of T2DM among AIs. Two studies indicated no relationship, and one noted an inverse relationship between SEP and the prevalence of T2DM. As a structural SDH factor, acculturation has been reported to play a mediating role in increasing the risk for T2DM among AIs in the US.

The majority of the studies that analyzed the relationship between structural and intermediary determinants indicated that higher SEP was related to healthier behaviors. One study noted a curvilinear trend in this relationship while another study indicated no relationship between SEP and healthy behaviors. Qualitative studies mentioned that cultural and social aspects of the AI community influence unhealthy behaviors that are linked to a higher prevalence of T2DM among AIs.

Physical inactivity, high carbohydrate intake, and metabolic syndrome were linked to increased prevalence of T2DM among AIs in numerous studies that addressed the relationship between intermediary SDH and prevalence of T2DM among AIs. An inverse relationship between carbohydrate intake and prevalence of T2DM was also noted in a couple of studies. Age and BMI also were linked to the prevalence of T2DM positively among AIs in multiple studies. In conclusion, the direction of relationships differed in the studies that analyzed the relationship between structural, intermediary SDH, and prevalence of T2DM among AIs.

References

1. Commodore-Mensah Y, Selvin E, Aboagye J, Turkson-Ocran RA, Li XM, Himmelfarb CD, et al. Hypertension, overweight/obesity, and diabetes among immigrants in the United States: an analysis of the 2010-2016 National Health Interview Survey. BMC Public Health. 2018;18.
2. Lee JWR, Brancati FL, Yeh H-c. Trends in the prevalence of type 2 diabetes in Asians versus Whites: Results from the United States National Health Interview Survey, 1997-2008.(ORIGINAL ARTICLE: Epidemiology/Health Services Research). Diabetes Care. 2011;34(2):353.
3. Kanaya AM, Herrington D, Vittinghoff E, Ewing SK, Liu K, Blaha MJ, et al. Understanding the high prevalence of diabetes in U.S. South Asians compared with four racial/ethnic groups: the MASALA and MESA studies. Diabetes care. 2014;37(6):1621.
4. Venkataraman R, Nanda NC, Baweja G, Parikh N, Bhatia V. Prevalence of diabetes mellitus and related conditions in Asian Indians living in the United States. Am J Cardiol. 2004;94(7):977-80.
5. American Diabetes Association. Statistics about Diabetes 2017 [Available from: http://www.diabetes.org/diabetes-basics/statistics/?loc=db-slabnav.
6. O'Keefe EL, DiNicolantonio JJ, Patil H, Helzberg JH, Lavie CJ, O'Keefe EL, et al. Lifestyle Choices Fuel Epidemics of Diabetes and
Cardiovascular Disease Among Asian Indians. Science direct. 2016;58(5).
7. Solar O, Irwin A. A Conceptual Framework for Action on the Social Determinants of Health Geneva: World Health Organization
2010.
8. Misra A, Ramchandran A, Jayawardena R, Shrivastava U, Snehalatha C. Diabetes in South Asians. Diabetic medicine : a journal of the British Diabetic Association. 2014;31(10):1153-62.
9. American Diabetes Association. Statistics about diabetes: American Diabetes Association; 2018 [Available from: http://www.diabetes.org/diabetes-basics/statistics/.
10. Rowley WR, Bezold C, Arikan Y, Byrne E, Krohe S. Diabetes 2030: Insights from Yesterday, Today, and Future Trends. Popul Health Manag. 2017;20(1):6-12.
11. Joo JY. Effectiveness of culturally tailored diabetes interventions for Asian immigrants to the United States: a systematic review. The Diabetes educator. 2014;40(5):605-15.
12. Batalova J, Zong J. Indian immigrants in the United States: Migration Policy Institute; 2017 [Available from: https://www.migrationpolicy.org/article/indian-immigrants-united-states.
13. Amutha A, Datta M, Unnikrishnan IR, Anjana RM, Rema M, Narayan KM, et al. Clinical profile of diabetes in the young seen between 1992 and 2009 at a specialist diabetes centre in South India. Prim Care Diabetes. 2011;5(4):223-9.
14. Shah VN, Mohan V. Diabetes in India: what is different? Curr Opin Endocrinol Diabetes Obes. 2015;22(4):283-9.
15. Shivane VK, Lila AR, Bandgar TR. Type 2 diabetic Asian Indians and COVID-19: Lessons learnt so far from the ongoing pandemic. J Postgrad Med. 2020;66(4):179-81.
16. Joshi SR. Type 2 diabetes in Asian Indians. Clin Lab Med. 2012;32(2):207-16.

17. World Health Organization. Social Determinants of Health: World Health Organization; 2008 [Available from: https://www.who.int/social_determinants/sdh_definition/en/.
18. Gujral UP, Narayan KM, Pradeepa RG, Deepa M, Ali MK, Anjana RM, et al. Comparing type 2 diabetes, prediabetes, and their associated risk factors in Asian Indians in India and in the U.S.: The CARRS and MASALA Studies. Diabetes Care. 2015;38(7):1312-8.
19. Gupta R, Deedwania PC, Sharma K, Gupta A, Guptha S, Achari V, et al. Association of Educational, Occupational and Socioeconomic Status with Cardiovascular Risk Factors in Asian Indians: A Cross-Sectional Study. Plos One. 2012;7(8):10.
20. Agrawal S, Ebrahim S. Prevalence and risk factors for self-reported diabetes among adult men and women in India: findings from a national cross-sectional survey. Public Health Nutr. 2012;15(6):1065-77.
21. Boddula R, Yadav S, Bhatia V, Genitta G, Pandey D, Kumar A, et al. High prevalence of type 2 diabetes mellitus in affluent urban Indians. Diabetes research and clinical practice. 2008;81(2):e4-7.
22. Nguyen AB, Moser R, Chou WY. Race and health profiles in the United States: an examination of the social gradient through the 2009 CHIS adult survey. Public Health. 2014;128(12):1076-86.
23. Gujral UP, Mohan V, Pradeepa R, Deepa M, Anjana RM, Mehta NK, et al. Ethnic variations in diabetes and prediabetes prevalence and the roles of insulin resistance and β-cell function: The CARRS and NHANES studies. 2016.
24. Misra A, Soares MJ, Mohan V, Anoop S, Abhishek V, Vaidya R, et al. Body fat, metabolic syndrome and hyperglycemia in South Asians. J Diabetes Complications. 2018;32(11):1068-75.
25. Kanaya AM, wasswl CL, Mathur D, Stewart A, D. H, J BM. Prevalence and correlates of diabetes in South Asian Indians in the United States: findings from the Metabolic Syndrome and Atherosclerosis in South Asians Living in America study and the Multi-Ethnic Study of Atherosclerosis. Metabolic syndrome and related disorders. 2010;8(2).
26. Shrivastava SR, Ghorpade AG. High Prevalence of Type 2 Diabetes Melitus and Its Risk Factors Among the Rural Population of Pondicherry, South India. Journal of research in health sciences. 2014;14(4):258-63.
27. Venkatesh S, Conner T, Song WO, Olson BH, Weatherspoon LJ. The Relationship Between Dietary Acculturation and Type 2 Diabetes Risk Among Asian Indians in the U.S. Journal of immigrant and minority health. 2017;19(2):294-301.
28. Joseph NM, Misra R, Wang J, Cron S, Ramaswamy P. Mediating Role of Acculturation and Lifestyle Behaviors on Cardiometabolic Risks among Asian Indians in the United States. Diabetes. 2018;67(Supplement 1):247-OR-OR.
29. Mehrotra N, Gaur S, Petrova A. Health Care Practices of the Foreign Born Asian Indians in the United States. A Community Based Survey. Journal of Community Health. 2012;37(2):328-34.
30. Denis Anthony, Rob Baggott, Judith Tanner, Kathryn Jones, Hala Evans, Gill Perkins, et al. Health, lifestyle, belief and knowledge differences between two ethnic groups with specific groups with specific reference to tobacco,diet and physical activity. Journal of Advanced Nursing. 2012.

31. Gadgil MD, Anderson CA, Kandula NR, Kanaya AM. Dietary patterns in Asian Indians in the United States: an analysis of the metabolic syndrome and atherosclerosis in South Asians Living in America study. J Acad Nutr Diet. 2014;114(2):238-43.
32. Fleming E, Carter B, Pettigrew J. The influence of culture on diabetes self-management: perspectives of Gujarati Muslim men who reside in northwest England. Journal of clinical nursing. 2008;17(5a):51-9.
33. Mukherjea A, Underwood KC, Stewart AL, Ivey SL, Kanaya AM. Asian Indian views on diet and health in the United States: importance of understanding cultural and social factors to address disparities. Fam Community Health. 2013;36(4):311-23.
34. Dhar S, Gor B, Banerjee D, Krishnan S, Dorai VK, Jones L, et al. Differences in nativity, age and gender may impact health behavior and perspectives among Asian Indians. Ethn Health. 2019;24(5):484-94.
35. Ram J, Selvam S, Snehalatha C, Nanditha A, Simon M, Shetty AS, et al. Improvement in diet habits, independent of physical activity helps to reduce incident diabetes among prediabetic Asian Indian men. Diabetes research and clinical practice. 2014;106(3):491-5.
36. Ghai NR, Jacobsen SJ, Van Den Eeden SK, Ahmed AT, Haque R, Quinn VP. A Comparison of Lifestyle and Behavioral Cardiovasular Disease Risk Factors Between Asian Indian and White Non Hispanic Man. Ethnicity and Disease. 2012;22(2):168-74.
37. Ram R, Goswami DN, Bhattacharya SK, Bhattacharya K, Saha BK, Saha J, et al. An epidemiological study on risk factors of diabetes mellitus among patients attending a medical college hospital in Kolkata, West Bengal. Journal of the Indian Medical Association. 2006;104(8):428-30.
38. Mukherjee S, Thakur G, Kumar BD, Mitra A, Chakraborty C. Long-term effects of a carbohydrate-rich diet on fasting blood sugar, lipid profile, and serum insulin values in rural Bengalis. Journal of diabetes. 2009;1(4):288-95.
39. Aravindalochanan V, Kumpatla S, Rengarajan M, Rajan R, Viswanathan V. Risk of diabetes in subjects with sedentary profession and the synergistic effect of positive family history of diabetes. Diabetes technology & therapeutics. 2014;16(1):26-32.
40. Radhika G, Sathya RM, Ganesan A, Saroja R, Vijayalakshmi P, Sudha V, et al. Dietary profile of urban adult population in South India in the context of chronic disease epidemiology (CURES-68). Public health nutrition. 2011;14(4):591-8.
41. Ye J, Rust G, Baltrus P, Daniels E. Cardiovascular risk factors among Asian Americans: results from a National Health Survey. Ann Epidemiol. 2009;19(10):718-23.
42. Fitzgerald N, Mathur S, Dutta S. P159 Participant Characteristics in a Community-Based Diabetes Education Program for South Asians. Journal of Nutrition Education and Behavior. 2020;52(7):S91-S2.
43. Nagarathna R, Kaur N, Anand A, Sharma K, Dada R, Sridhar P, et al. Distribution of glycated haemoglobin and its determinants in Indian young adults. Diabetes Res Clin Pract. 2020;159:107982.
44. Vijayakumar G, Manghat S, Vijayakumar R, Simon L, Scaria LM, Vijayakumar A, et al. Incidence of type 2 diabetes mellitus and prediabetes in Kerala, India: results from a 10-year prospective cohort. BMC Public Health. 2019;19(1):140.
45. Ghorpade A, Majgi S, Sarkar S, Sekhar Kar S, Roy G, Ananthanarayanan P, et al. Diabetes in rural Pondicherry, India: a population-based study of the incidence and risk factors. WHO South-East Asia journal of public health. 2013;2(3-4):149-55.

46. He L, Tuomilehto J, Qiao Q, Söderberg S, Daimon M, Chambers J, et al. Impact of classical risk factors of type 2 diabetes among Asian Indian, Chinese and Japanese populations for the DECODA study group. Diabetes & Metabolism. 2015;41:401-9.
47. Bajaj HS, Pereira MA, Anjana RM, Deepa R, Mohan V, Mueller NT, et al. Comparison of relative waist circumference between Asian Indian and US adults. J Obes. 2014;2014:461956.
48. Ramachandran A, Snehalatha C, Vijay V. Temporal changes in prevalence of type 2 diabetes and impaired glucose tolerance in urban southern India. Diabetes research and clinical practice. 2002;58(1):55-60.
49. Daniel M, Wilbur J, Marquez D, Farran C. Lifestyle Physical Activity Behavior Among South Asian Indian Immigrants. Journal of Immigrant and Minority Health. 2013;15(6):1082-9.
50. Gadgil MD, Anderson CAM, Kandula NR, Kanaya AM. Dietary patterns are associated with metabolic risk factors in South Asians living in the United States. The Journal of nutrition. 2015;145(6):1211-7.

Hypotheses

The following hypotheses were tested to determine the relationship between structural and intermediary determinants and the diagnosis of DS among AIs in New Jersey:

Primary Hypothesis. AIs in NJ at a higher SEP (education, occupation, income, homeownership, internet use) will have a lower diagnosis of DS than the AIs in NJ at a lower SEP.

Exploratory Hypothesis 1. AIs in NJ who follow healthier behaviors (higher fruit and vegetable intake, lower tobacco and alcohol consumption, higher physical activity) and have higher levels of health care access will have a lower diagnosis of DS than the AIs in NJ who do not follow healthier behaviors.

Exploratory Hypothesis 2. Healthier behaviors (higher fruit and vegetable intake, lower tobacco and alcohol consumption, lower physical activity) mediate the relationship between higher SEP and lower rates of DS diagnosis among AIs in NJ.

Exploratory Hypothesis 3. Higher levels of health care access mediate the relationship between higher SEP and lower rates of DS diagnosis among AIs in NJ.

CHAPTER 3: METHODS

This study used a cross-sectional, secondary analysis of the New Jersey (NJ) *Behavioral Risk Factor Surveillance System* (BRFSS) data for the years 2013 to 2017 (CDC). The study included de-identified data obtained from the New Jersey Department of Health (NJDOH). The study has been reviewed and approved by Institutional Review Boards (IRBs) of Rutgers University and the NJDOH proxy - Rowan University. The approval letters from Rutgers and Rowan Universities are provided in Appendix 5 and 6 respectively.

A series of logistic regressions were conducted to analyze the relationships between the structural SDH, intermediary determinants, and the diagnosis of T2DM, PDM, & DS. Logistic regression analyses were conducted to examine which category of factors had the most substantial impact on the prevalence rates for T2DM, PDM, & DS among Asian Indians (AI). Mediation analyses were conducted to examine if the intermediary determinant factors mediated the relationship between the structural SDH factors and the prevalence of DS.

The Research Setting – Data Source

The BRFSS is a telephone survey conducted among the people of the US. De-identified BRFSS data sets are available online for public use. This secondary data analysis required data on AIs which was collapsed into the major category of Asian Pacific Islanders in the publicly available data sets. For this reason, the distinctive data for the AIs was requested from the NJDOH after additional IRB approval from Rowan University that was required by NJDOH.

The BRFSS survey follows a disproportionate stratified sampling (DSS) design. Sampling is based on sub-state geographic regions. Stratified sampling, as opposed to simple random sampling, reduced the margins of error by decreasing the chance for unequal selection probabilities for some population subsets (Anderson & Fricker). The DSS is a complex sampling design in which the respondents have different sampling weights. Sampling weight is the inverse of the sampling probability (Anderson & Fricker). Sampling weight corresponds to the number of people in a population that one participant represents (Anderson & Fricker). The BRFSS interviews included both landline and cellular telephone surveys. This dual frame approach increased the data quality, validity, and representativeness of the data (CDC, 2016). The state of NJ followed the same procedures.

The median response rate (i.e., the proportion of the number of people who completed the survey and those who are eligible) was 45.1% (range 30.6%-64.1%) in 2017 (CDC, 2018). According to the 2017 BRFSS data quality summary report, the BRFSS survey response rates are among the highest of all national surveys in the US (CDC, 2018). This study included all the AIs in the NJ BRFSS survey data from 2013 to 2017 to ascertain an appropriate sample size for this analysis.

The BRFSS is the largest continuously conducted health survey in the world. BRFSS conducts more than 400,000 interviews every year. Established in 1984, the BRFSS survey yields state and local data from all 50 states and official territories of the US (CDC, 2019). The purpose of the BRFSS questionnaire is to assess the health-related risk factors of individuals. A group of researchers including the state representatives update the BRFSS survey questions every year as per the current and emerging needs of health care.

The BRFSS questionnaire is a health-related national survey of US residents which explores their health-related behaviors, chronic disease conditions, and the use of preventive health care. The information gleaned from the BRFSS survey guides numerous national health promotion and disease prevention activities.

The Study Sample

The sample for this study was included adult AIs, greater than 18 years of age living in New Jersey, who were self-identified as AIs in the BRFSS survey from 2013-2017 in the NJDOH data set. Individuals less than 18 years of age were excluded from participation since the study is focused on T2DM, and T2DM commonly occurs at a later age as opposed to T1DM. This delimitation is likely to reduce the chance for the inclusion of participants with T1DM. Participants who have gestational diabetes also were excluded from the study. Specific syntax used to separate the AIs in the data set is provided in Appendix 2.

A sample size calculator (*Odds ratio-sample size*, 2019) was used to calculate the recommended sample size. Five inputs for the calculation were the relative precision, significance level, absence case prevalence, expected odds ratio, and presence to absence ratio. Presence and absence groups are the groups who have the presence or absence of average family income >$75,000. The odds ratio is the odds of having T2DM given the presence group relative to the same outcome in the absence group. The ratio of the number of presences compared to the number of absences is represented as the presence to absence ratio.

The calculation was conducted based on relative precision of 50%, the confidence level was 95%, the absence case prevalence of 11.2%, the expected odds ratio of 0.66, and the presence to absence ratio of 1.97. Based on the estimates provided by Kanaya et al. (2010) for the predictor income, the odds ratio was 0.66 and the sample size was calculated to be 411 for the most conservative prevalence rate of 11.2%. This number includes the sample size for the low-income (*n* =138) and high-income (*n* =273) groups (*Odds ratio-sample size*, 2019). For the predictor education, the odds ratio was 0.71 and the sample size was calculated to be *N* = 373 for a prevalence rate of 11.2%. Odds ratios for other correlates were not available in the literature.

Calculating sample size based on the formula N=20 times k/p (where N-sample size; k-number of predictors; p-proportion of success) also considers the number of variables in the study. This method yielded the sample size for the proposed study as N=20*(13)/0.5=520. The calculated sample size was also found to be adequate according to the model for sample size calculation for observational studies using logistic regression analysis for a large population (Bujang et al., 2018).

The NJ data set obtained for the study included 1,132 AIs, which provided an adequate sample size for the analyses except for some behavioral variables and prediabetes. Some core questions in the NJ-BRFSS questionnaire are rotated every odd and even number of years. Thus, even though the dataset included five years of data and a sample size of 1,132, only 2 out of those 5 years comprised of the optional modules. Prediabetes was included in the optional modules in 2014 and 2017 and fruit and vegetable intake variables were included only in the year 2017. The sample size for those variables was 421. This led to reduced crosstabulation cell sizes for some behavioral variables in the study.

The Study Instrument - *BRFSS Questionnaire*

The BRFSS questionnaire uses mostly a multiple-choice answer format. The survey includes core questions, optional modules, and state-added modules (CDC, 2016). Core questions are standard for all states. Some core questions are rotated every even and the odd number of years. Individual states can choose their optional modules on a specific topic that is important to them. The state-added questions are not evaluated or tracked by BRFSS (CDC, 2016). State added modules included in the study were prediabetes in the years 2014 and 2017. Some behavioral variables in this study such as fruit and vegetable intake were included only in the year 2017. More than a hundred studies have established the reliability and validity of this questionnaire (Pierannunzi et al., 2013).

Reliability. A systematic review of studies assessed and reported the reliability and validity of the BRFSS questionnaire (Pierannunzi et al., 2013). The test-retest method, the reliability of questions when there is a change in the order of questions and reliability of questions over a period, was the primary method used to assess the reliability of the BRFSS questionnaire (Pierannunzi et al., 2013). This review reported high rates of test-retest reliability (>0.80) for the BRFSS questionnaire. This review also reported moderate to high correlations in inter-rater reliability tests with kappa values ranging from 0.40 to 0.86. In the group of vigorous physical activity, kappa values were >0.60, demonstrating a substantial correlation. Interclass Correlation Coefficient (ICC) for placing the respondents into groups of vigorously active, moderately active, or inactive activity ranged from 0.32 to 0.85. The physical activity enjoyment questionnaire also had high internal consistency; Cronbach's alpha ranges from 0.89-0.96 (Bopp et al., 2006).

Validity. Face validity is the subjective assessment by the experts and the individuals from the target population about the content of the instrument (Newschaffer & Counte, 1998). Content validity refers to the representativeness of the items of an instrument to the concept it measures (Newschaffer & Counte, 1998). The expert panel consensus process that developed the BRFSS questionnaire has confirmed that the BRFSS questionnaire possesses face and content validity (Newschaffer & Counte, 1998).

To assess the concurrent criterion-related validity, researchers compared the BRFSS questionnaire with other self-reported comprehensive health scales. Comparison of the BRFSS with the surveys such as NHANES and NHIS showed some variance in the measurements, however were all in agreement with trends (Pierannunzi et al., 2013). There was a substantial agreement between the Occupational Physical Activity Questionnaire (OPAQ) and the BRFSS (kappa=0.71). Comparison with physical measures such as accelerometer was also used for demonstrating criterion-related validity of the BRFSS scale. Collectively from these findings, it is evident that the BRFSS questionnaire has a moderate to high reliability and validity. The significant weaknesses of the BRFSS questionnaire are that it is a very long questionnaire with multiple sections and subsections and research did not sufficiently test all the sections of this questionnaire.

Procedure for Data Collection

State health personnel or contractors administer the BRFSS questionnaires with the use of Computer Assisted Telephone Interview Systems. However, some states conduct in-house surveys. In-house surveys have been found to have a better response rate. The interviewers get repeated training from the state coordinator or interviewer supervisor to maintain the consistency and quality of data collection (CDC, 2016).

The interviewers are also evaluated for their performance. The evaluation process involves verification callbacks and direct monitoring of the interviewers (CDC, 2016). Similarly, contractors conducting the interviews for the state also have a consistent method of systematically monitoring the performance of the interviewer. Moreover, the state quantifies the interviewer's performance (CDC, 2016). The interviews are conducted seven days per week during days and evening hours. Each interview is approximately 23-28 minutes long with the core questions taking an average of 18 minutes and the state-added questions about five to ten minutes depending on the number of questions added (CDC, 2016).

Upon completion of the interview and data collection by state health personnel, states transmit the data to the CDC for processing. The CDC then provides the edited and weighted data back to the states after analysis, along with a data quality report (CDC, 2016). Most of the BRFSS data is publicly available with a unique ID variable to avoid the identification of the participants. Data of some racial/ethnic groups with a smaller number of participants are collapsed to protect the participant identification. Retrieving this data for further research requires special permission from the CDC.

The minority group of AIs is collapsed to the racial category of Asian/Pacific Islanders to prevent participant identification in the BRFSS data set that is publicly available. For this research, the data specifically on AIs was obtained through NJDOH. A comprehensive research proposal with a list of required variables, including restricted variables, was submitted to the NJDOH to obtain datasets that specify AI as an ethnic group in the data variables. A representative from NJDOH worked with the author and provided the de-identified data that specified AIs.

Operational Definitions

The independent variables of this study were categorized into structural and intermediary determinant variables, as shown in Table 1. Structural SDH was operationalized with the items in the BRFSS survey that measure income, education, employment, homeownership, and internet use. Participants with a family income greater than or equal to $75,000 were considered of higher SEP and participants with a family income less than $75,000 were considered of lower SEP. This classification is based on the study which was the basis for the sample size calculation of this project (Kanaya et al., 2014). Intermediary determinants were operationalized with the items in the BRFSS questionnaire that measured fruit and vegetable intake, smoking, alcohol intake, exercise, and access to health care factors. The BMI variable was calculated using self-reported height and weight variables using the formula BMI= weight (lb.) / [height (in)]^2 x 703 (CDC, 2020). The specific BRFSS items corresponding to each of the study variables are listed in Table 2.

Table 1

Social Determinants of Health Variables

Structural Determinants of Health	Intermediary Determinants of Health	Demographic factors
Education	BMI	Gender
Employment	**Behavioral factors**	Age
Income	Fruit and vegetable intake	Marital Status
Homeownership	Tobacco/ alcohol consumption	
Internet use	Exercise	
	Access to care factors	
	Health plan	
	Medical check-up	
	Personal doctor	
	Medical cost	

The dependent variables of the study were the diagnosis of T2DM, PDM, and DS. The dependent variables were operationalized as single questions for each of the disease states in the BRFSS questionnaire, asking if they have ever had a diagnosis of T2DM and PDM. The questions and answer choices in the questionnaire corresponding to this study variables are shown in Table 2. Participants who responded positively to either one of the T2DM or PDM questions were categorized as positive for diabetic status (DS). The links to BRFSS questionnaires from 2013 to 2017 are provided in Appendix 4.

Table 2

Questions and answer categories for variables

Variables	Original Categories	Binary categories
Demographic Variables		
Are you … ,	1 Male	0 Male
	2 Female	1 Female
	9 Refused	
What is your age? ,	_ _ Code age in years	0 18-44 years
	07 Don’t know / Not sure	1 >44 years
	09 Refused	
Are you…? ,	1 Married	0 Not Married/living alone
	2 Divorced	
	3 Widowed	
	4 Separated	1 Married, living together
	5 Never married, or	

Variables	Original Categories	Binary categories
	6 A member of an unmarried couple 9 Refused	
SEP variables		
Is your annual household income from all sources—,	04 Less than $25,000 03 Less than $20,000 02 Less than $15,000 01 Less than $10,000 05 Less than $35,000 06 Less than $50,000 07 Less than $75,000 08 $75,000 or more 77 Don’t know / Not sure 99 Refused	0 < 75K/year 1 >/= 75K/year
Are you currently…?	1 Employed for wages 2 Self-employed 3 Out of work for 1 year or more 4 Out of work for less than 1 year 5 A Homemaker 6 A Student 7 Retired, or 8 Unable to work Do not read: 9 Refused	0 Not Employed 1 Employed
What is the highest grade or year of school you completed?	1 Never attended school or only attended kindergarten 2 Grades 1 through 8 (Elementary) 3 Grades 9 through 11 (Some high school) 4 Grade 12 or GED (High school graduate) 5 College 1 year to 3 years (Some college or technical school) 6 College 4 years or more (College graduate) 9 Refused	0 Below High School 1 High School/College
Do you own or rent your home?	1 Own 2 Rent 3 Other arrangement 7 Don’t know / Not sure 9 Refused	0 Rent/Other 1 Own
Have you used the internet in the past 30 days?	1 Yes 2 No 7 Don’t know / Not sure 9 Refused	0 No 1 Yes
Intermediary determinants		
Have you smoked at least 100 cigarettes in your entire life?	1 Yes 2 No 7 Don’t know / Not sure 9 Refused	0 No 1 Yes

Variables	Original Categories	Binary categories
During the past 30 days, how many days per week or per month did you have at least one drink of any alcoholic beverage such as beer, wine, a malt beverage, or liquor?	1 _ _ Days per week 2 _ _ Days in past 30 days 888 No drinks in past 30 days 777 Don't know / Not sure 999 Refused	0 None 1 > 1 day
Considering all types of alcoholic beverages, how many times during the past 30 days did you have X [CATI NOTE: X = 5 FOR MEN, X = 4 FOR WOMEN] or more drinks on an occasion?	_ _ Number of times 88 None 77 Don't know / Not sure 99 Refused	0 None 1 > 1 day
Not including juices, how often did you eat fruit? You can tell me times per day, times per week or times per month.	1_ _ Days 2_ _ Weeks 3_ _ Months 888 Never 777 Don't Know 999 Refused	0 None 1 > 1 Times/day
How often did you eat a green leafy or lettuce salad, with or without other vegetables?	1_ _ Days 2_ _ Weeks 3_ _ Months 888 Never 777 Don't Know 999 Refused	0 None 1 >1 Times/day
Not including lettuce salads and potatoes, how often did you eat other vegetables?	1_ _ Days 2_ _ Weeks 3_ _ Months 888 Never 777 Don't Know 999 Refused	0 None 1 >1 Times/day
During the past month, other than your regular job, did you participate in any physical activities or exercises such as running, calisthenics, golf, gardening, or walking for exercise?	1 Yes 2 No 7 Don't know / Not sure 9 Refused	0 No 1 Yes
Access to health care variables		
Do you have any kind of health care coverage, including health insurance, prepaid plans such as HMOs, government plans such as Medicare, or Indian Health Service?	1 Yes 2 No 7 Don't know / Not sure 9 Refused	0 No 1 Yes
Do you have one person you think of as your personal doctor or health care provider? Clarify: If "No" ask: "Is there more than one, or is there no person who you think of as your personal doctor or health care provider?"	1 Yes, only one 2 More than one 3 No 7 Don't know / Not sure 9 Refused	0 No 1 Yes
Was there a time in the past 12 months when you needed to see a doctor but could not because of cost?	1 Yes 2 No 7 Don't know / Not sure 9 Refused	0 No 1 Yes

Variables	Original Categories	Binary categories
A routine checkup is a general physical exam, not an exam for a specific injury, illness, or condition. About how long has it been since you last visited a doctor for a routine checkup?	1 Within the past year (anytime less than 12 months ago) 2 Within the past 2 years (1 year but less than 2 years ago) 3 Within the past 5 years (2 years but less than 5 years ago) 4 5 or more years ago 7 Don't know / Not sure 8 Never 9 Refused	0 No 1 Yes
Outcome variable		
Have you (Ever told) you have diabetes?	1 Yes 2 Yes, but female told only during pregnancy 3 No 4 No, pre-diabetes or borderline diabetes 7 Don't know / Not sure 9 Refused	0 No 1 Yes
Have you (Ever told) you have prediabetes?	1 Yes 2 Yes, during pregnancy 3 No 7 Don't know / Not sure 9 Refused	0 No 1 Yes

Data Analysis

The SAS computer programming version 9.4 was used to conduct data analysis in this study. An alpha value of 0.05 was set to control for Type I error. Type II error was controlled by setting power of 0.80. The SAS codes or syntax used for statistical analyses are provided in Appendix 2. Variance Inflation Factor was used to examine the presence of any multicollinearity among the study predictors. The results are shown in Appendix 3. Based on these analyses, tests of collinearity for study predictors were within acceptable parameters (Agresti & Finlay, 1986), with the variance inflation factor (VIF) values below two.

Univariate/ Descriptive analysis of the study variables

Data analysis for this study was conducted in three stages. The first stage of the data analysis was univariate analysis. The univariate analysis described and summarized the study variables and characteristics of the sample. The univariate or descriptive analysis was conducted using frequencies, weighted frequencies, and proportions for the study variables since the variables were categorical.

The de-identified NJ-BRFSS datasets for five years from 2013 to 2017 were combined into one dataset by using the Microsoft Access program software. Dummy variables were used to convert continuous variables to categorical variables and to modify several of the categorical variables. The use of dummy variables was intended to conduct meaningful analyses and to maintain consistency. Data were recoded to assign missing values.

The PROCSURVEY FREQ command in the SAS computer program was used to conduct weighted analyses of the combined data set in SAS. Proper weighing of the data was executed to obtain the results representative of AIs in the state of New Jersey using the strata, cluster, and weight variables that were provided in the datasets. The strata, cluster, and weight variables were _Geostr, _Psu, and _Llcpwt respectively. Syntaxes are provided in Appendix 2.

Bivariate Analysis

The second stage of data analysis was bivariate analyses. In this study, cross-tabulations and Chi-square tests were used to examine the associations between the outcomes and independent variables. For the bivariate analysis, the statistical command PROC SURVEYFREQ was used to cross-tabulate and conduct Chi-square tests. The Chi-square test was appropriate since the variables were categorical. Alpha value was set to <.05 for the bivariate analyses. Crosstabulation cell sizes of some variables fell below the required level of 30 which could affect the validity of the estimates.

Multivariate Analysis

The third stage of the statistical analysis included a multivariate analysis. Since the dependent variables were categorical, logistic regression was the technique used for multivariate statistical analysis in this study. Regression analysis controls the effect of covariates while testing the relationships between study variables (Salkind, 2014). Relationships that had a *p*-value less than 0.3 in the bivariate analysis were included in the logistic regression analysis to test the hypotheses. The SAS Statistical command PROC SURVEYLOGISTIC was used to conduct weighted logistic regression analysis. The regression analysis was used to construct the best fitting, and parsimonious model to describe the explanatory power of the SEP and intermediary factors on the diagnosis of T2DM. The test of the overall model was a likelihood ratio chi-square. Alpha was set to <.05.

Mediation Analysis

Mediation analysis was conducted to examine whether health-related behaviors and access to care variables mediate the relationship between SEP and the prevalence of T2DM among AIs in NJ, as shown in Figure 2. Sample weights were taken into account for the mediation analysis.

Figure 3

Mediation analysis model

Figure 1a

$$X \xrightarrow{\quad a \quad} M \xrightarrow{\quad b \quad} Y$$

Figure 1b

$$X \xrightarrow{\qquad\quad c \qquad\quad} Y$$

Figure 1c

$$X \xrightarrow{\qquad\quad c' \qquad\quad} Y$$

$$M \xrightarrow[\quad b \quad]{} Y$$

Baron and Kenny in 1986 initially defined mediation analysis and described the methods to conduct mediation analysis (Baron & Kenny, 1986). In the above figures, X is the predictor, Y is the outcome and M is the intervening variable or the mediator. a, b, and c are the regression coefficients in the analysis. *a* is the regression coefficient when M is regressed on X and b is the regression coefficient when Y is regressed on M. Also, c is the regression coefficient when Y is regressed on X while c' is the regression coefficient when M is controlled (Iacobucci, 2012).

In the mediation analysis of Baron and Kenny (1986), mediation is present if both predictor and mediator predict the outcome and the predictor impacts the outcome through the mediator (Baron & Kenny, 1986). According to this model full mediation is indicated by elimination of the relationship between the predictor and outcome when the mediator is controlled. In other words, the c' in figure 1c will be non-significant for full mediation. Partial mediation is indicated by the reduction in the relationship between the predictor and the outcome.

There are some flaws to Baron and Kenny's model including the fact that this model does not test the significance of the indirect effect (MacKinnon, 2008). Several statisticians introduced methods to solve this problem. As per MacKinnon, the indirect effect coefficient i.e., the difference between the regression coefficients c and c', is equivalent to the product of regression coefficients *a* and *b*. Mediation is indicated in this model if the products of the two coefficients are significant (MacKinnon, 2008).

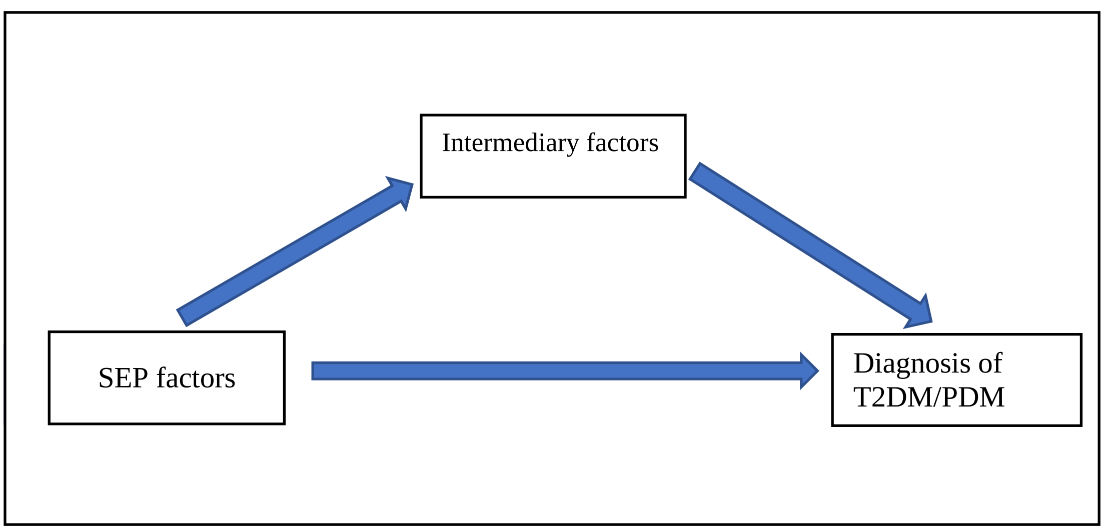
To analyze the mediation effect of discrete mediators, proc causalmed in SAS was used to conduct mediation analysis in this study. Causalmed procedure estimated the direct and indirect effects in mediation analysis from observational data. This mediation analysis was more general and was developed to address the situation of discrete mediators and discrete outcomes when the Baron and Kenny model failed. Proc causalmed was equipped to conduct this analysis with multiple mediators and covariates that are binary or continuous (Valeri & VanderWeele, 2013; VanderWeele, 2014).

An acyclic graph represented the mediation model in this study (Fig.3). Mediation analysis was performed for the access to care factors (having a personal doctor and more than one medical check-up in the last two years) which had a statistically significant relationship with the diagnosis of T2DM and PDM in the regression analysis when access to care variable was the exposure variable and the diagnosis of T2DM and PDM were the outcome variable. In the mediation analysis, personal doctor and medical check-ups were assessed as the mediators, having internet and age >44 years were the exposure variable, and the diagnosis of T2DM, PDM, and DS were the outcome variables.

The mediation analysis was conducted by using the PROC CAUSALMED procedure in the SAS software package. PROC CAUSALMED computed four main causal mediation effects and they were, total effect (TE), controlled direct effect (CDE), natural direct effect (NDE), and natural indirect effect (NIE). For example, CDE was the effect of the internet on the diagnosis of T2DM when the personal doctor was held at a given level corresponding to not having internet usage (setting the exposure is at the intervention level). NIE is the effect of a personal doctor when the internet use was held at the value corresponding to the presence of internet usage (setting the exposure to the intervention level). This provided the effect of the internet on the diagnosis of T2DM through personal doctor. The TE is always the sum of NDE and NIE. The effects are computed on the odds ratio scale since the variables are binary (Valeri & VanderWeele, 2013).

Figure 4

Acyclic graph of the proposed mediation model



Two-way decompositions of PROC CAUSALMED included NDE + NIE (natural direct effect and natural indirect effect); CDE + PE (controlled direct effect and portion eliminated), and TDE + PIE (total direct effect and pure indirect effect). The total direct effect was the sum of the effect of the internet on the diagnosis of T2DM when the mediator personal doctor variable was held at the values corresponding to not using the internet. PE was the difference between the total effect of the internet on the diagnosis of T2DM and the controlled direct effect of the internet on the diagnosis of T2DM when the personal doctor factor was held at a given level. PIE was the effect of personal doctor on the diagnosis of T2DM in the absence of internet use.

The four-way decomposition was used to further distinguish mediated and interaction effects. PROC CAUSALMED computed a four-way decomposition that included four effect components. The four-way decomposition effects were, controlled direct effect (CDE) (the component that is due neither to interaction nor mediation), reference interaction (IRF or INTref) (the component that is due to interaction but not mediation), mediated interaction (IMD or INTmed) (the component that is due to both interaction and mediation), pure indirect effect (PIE) (the component that is due to mediation but not interaction) (VanderWeele, 2014).

The Weighting of the Data

Inclusion of additional demographic characteristics by using a weighting methodology called ‘raking’(iterative proportional fitting) allowed the data to properly reflect the socio-demographic composition of individual states in the country during survey analysis of BRFSS data (CDC, 2016). Raking uses known population totals from the census tract and involves estimating weights across the various set of variables repeatedly until the weights stop changing and become constant. BRFSS data analysis provides for the weighting of the data allowing the proper representation of each population subsets. However, retrieving the data only for the AI subset in NJ made the results representative of AIs in NJ, not of the entire US.

CHAPTER 4: STUDY RESULTS

The purpose of this study was to examine the impact of social determinants of health on the diagnosis of type 2 Diabetes Mellitus (T2DM) or prediabetes (PDM) among Asian Indians (AIs) living in New Jersey (NJ). The Behavioral Risk Factor Surveillance System (BRFSS) datasets from the year 2013 to 2017 for the state of NJ were used to investigate these relationships. The analyses included structural social determinants and intermediary determinants of health in association with the diagnosis of T2DM, PDM, and having either T2DM or PDM i.e., diabetes status (DS). Results of the data analyses are presented in this chapter.

Characteristics of the Study Sample

The study sample included 1,132 AI individuals, which was equivalent to 1,534,438 AI individuals in the State of NJ when the data were weighed appropriately. In the sample, 63% of the participants were 18 to 44 years of age and 37% were 45 years and above. The gender of the participants was evenly distributed. The BMI was mostly in the obese/overweight category (69%). Most of the participants were married (79%), had family income >$75,000 per year (60%), owned a house (26%), were employed (70%) and had a high school education or higher (80%). The use of the internet was reported by 94% of the participants.

More than 80% of the participants in this study had responded positively to all the access to care variables. Most of the participants followed healthier behaviors such as fruit intake (68%), vegetable intake (69%), and green vegetable intake (33%). Exercise in the last 30 days was reported by 68% of the sample. Forty-two percent (42%) reported consuming alcohol. Binge drinking was present in 18% of the sample. About 13% of the sample reported smoking in the last 100 days.

Regarding the outcome variables, 10% reported having been diagnosed with T2DM, and 16% reported having been diagnosed with either T2DM or PDM (described in this study as diabetes status - DS) in the total sample. Among the respondents of the optional module for prediabetes, 16% reported having been diagnosed with PDM. This comes to about 6% of the total sample. The percentage of missing data was less than 10% for most of the study variables, except for income (17%), binge drinking (61%), fruit intake (82%), green vegetable intake (82%), other vegetable intakes (83%), and PDM status (63%). Characteristics of the study sample are summarized in Table 3.

Table 3

Distribution of demographic, SEP, intermediary, and access to care variables (n=1,132)

Variables			Raw frequency *(n)*	Weighted frequency *(n)*	Percent[a] (%)	Valid Percent[a] (%)
Demographic variables	Age in years (M=41.5; SD=14.28	18-44	697	960,474	61.61	63.35
		> 44 years	413	555,589	36.45	36.65
		Missing	22	5,556	1.94	
	Sex	Male	672	786,169	51.24	51.24
		Female	460	748,269	48.77	48.76
		Missing	0	0	0	
	Marital status	Not Married/living alone	236	341,062	20.83	22.33
		Married, living together	886	1,186,309	78.29	77.67
		Missing	10	13,440	0.88	
SEP variables	Income	<75K/year	367	505,156	32.39	39.82
		>/=75K/year	577	763,319	51.02	60.18
		Missing	188	210,440	16.59	
	Education	Below High School	114	230,045	10.06	15.09
		High School/College	1010	1,294,919	89.23	84.91
		Missing	8	10,688	0.71	
	Employment	Not Employed	292	423,429	25.77	27.82
		Employed	826	1,098,672	72.99	72.18
		Missing	14	18,874	1.24	
	Home ownership	Rent/Other	670	1,072,963	59.14	73.58
		Own	404	461,475	35.75	26.42
		Missing	58	78,563	5.12	
	Internet use	No	70	96,633	6.18	6.34
		Yes	1016	1,398,579	89.76	93.66
		Missing	46	60,705	4.06	
Access to care variables	Health coverage	No	95	146,039	8.38	9.02
		Yes	1032	1,388,399	91.17	90.98
		Missing	5	6,751	0.44	
	Routine checkup in last 2 years	No	75	142,052	6.62	7.10
		Yes	1022	1,392,386	90.20	92.90
		Missing	36	48,795	3.18	
	Missing medical help due to cost in last year	No	1015	1,393,066	89.67	90.71
		Yes	107	141,372	9.44	9.29
		Missing	10	13,503	0.88	
	Personal doctor	No	228	281,462	20.21	17.96
		Yes	897	1,252,976	79.17	82.04
		Missing	7	9,513	0.62	
Intermediary variables	BMI (M=24.56; SD=4.19)	Normal/Underweight	337	471,649	30.74	30.74
		Obese/Overweight	795	1,062,789	69.26	69.26
		Missing	N/A	N/A	N/A	
	Alcohol consumption in last 30 days	None	572	933,596	50.49	57.65
		> 1day	451	600,842	39.81	42.35
		Missing	110	148,993	9.71	
	Binge drinking in last 30 days	None	368	1,430,303	32.48	82.29
		> 1day	76	104,135	6.71	17.71
		Missing	689	933,091	60.81	
	Smoked in last 100days	No	879	1,255,753	77.58	87.02
		Yes	165	187,366	14.56	12.98
		Missing	89	113,429	7.86	
	Exercise last 30 days	No	251	351,485	22.15	32.51
		Yes	795	1,090,855	70.26	67.49
		Missing	86	109,473	7.59	
	Fruit frequency	None	72	100,242	6.35	32.51

Variables			Raw frequency *(n)*	Weighted frequency *(n)*	Percent[a] (%)	Valid Percent[a] (%)
		> 1Times/day	129	208,116	11.39	67.49
		Missing	932	253,655	82.26	
	Green veg frequency	None	123	205,790	1.86	66.87
		> 1Times/day	77	101,954	6.80	33.13
		Missing	933	253,427	82.35	
	Other veg frequency	None	65	94,470	5.74	30.87
		> 1Times/day	133	211,549	11.74	69.13
		Missing	935	252,526	82.52	
Outcome variables	Diabetes (T2DM)	No	1022	1,386,502	90.36	90.36
		Yes	110	147,937	9.64	9.64
		Missing	0	0	0	
	Prediabetes (PDM)	No	362	493,893	31.95	84.39
		Yes	69	91,343	5.21	15.61
		Missing	712	367,762	62.84	
	Diabetes status (DS)	No	953	1,295,158	84.41	84.41
		Yes	179	239,280	15.59	15.59
		Missing	N/A	N/A	N/A	

[a] Proportions were calculated based on weighted frequencies

Determinants of Type 2 Diabetes Mellitus (T2DM)

Bivariate Analyses

Bivariate analyses, using Chi-square, revealed that having a T2DM diagnosis was statistically significantly associated with age, BMI, income, internet use, having a personal doctor, and vegetable intake (Table 4). More specifically, having a T2DM diagnosis was significantly higher among older AIs (X^2 = 21.286, p = <.001) and those with an obese/overweight BMI (X^2 = 14.236, p = 0.04) and lower-income (X^2 = 7.13, p = <.008). Having a T2DM diagnosis was also significantly higher among AIs who use the internet (X^2 = 10.69, p = .001) and those who have a personal doctor (X^2 = 14.8, p = <.001) and who have >1 time/day and with other vegetable intakes (X^2 = 6.82, p = .009).

Table 4

Associations between having a T2DM diagnosis, and the demographic, SEP, access to care, and intermediary variables (n=1,132).

	Correlates	Outcome	Having a T2DM diagnosis			Having No T2DM diagnosis			X^2 (P)
			Raw n	Weight-ed n	Row %	Raw n	Weight-ed n	Row %	
Demographic and SEP variables	Age	18-44	30	46062	31.2	667	914412	66.8	21.286(<.001)
		>44years	79	101380	68.8	334	454209	33.1	
	Sex	Male	78	86821	58.7	594	699348	50.4	1.079(.299)
		Female	32	61116	41.3	428	687153	49.6	
	Marital Status	Not Married/living alone	22	27231	18.5	214	313832	22.7	0.360(.548)
		Married living together	86	120104	81.5	800	1066205	77.3	
	Income	<75K/year	48	70410	57.2	319	434746	38	7.129(.008)
		>/=75K/year	50	52706	42.8	527	710614	62	
	Education	Below high school	14	26539	18.1	100	203505	14.8	0.29(.590)
		High school/college	95	120347	81.9	915	1174571	85.2	
	Employment	Not employed	38	49165	33.4	254	374265	27.2	0.812(.367)
		Employed	70	98170	66.6	756	1000502	72.8	
	Home ownership	Rent/other	77	109939	81.3	593	963023	72.8	2.383(.123)
		Own	27	25231	18.7	377	360079	27.2	
	Internet	No	13	25531	18	57	69170	5.1	10.694(.001)
		Yes	88	115928	82	928	1282651	94.9	
Access to care variables	Health plan	No	9	13901	9.4	86	123776	9	0.009(.926)
		Yes	101	134036	90.6	931	1254363	91	
	Routine checkup in last 2 years	No	2	3429	2.4	73	103011	7.6	2.624(.105)
		Yes	104	140784	97.6	918	1251603	92.4	
	Missed medical help due to cost	No	94	130298	90.5	921	1249920	90.7	0.004(.953)
		Yes	13	13632	9.5	94	127740	9.3	
	Personal Doctor	No	7	6592	4.5	221	267642	19.4	14.802(<.001)
		Yes	103	141345	95.5	794	1111630	80.6	
Intermediary variables	BMI	Normal/underweight	31	29708	20.1	306	441941	31.9	4.236(.040)
		Obese/overweight	79	118229	79.9	716	944560	68.1	
	Alcohol days in last 30 days	0	62	93001	66.2	510	724824	56.7	1.536(.215)
		>1day	38	47564	33.8	413	553278	43.3	
	Binge drinking in last 30 days	0	31	37249	78.3	337	446724	82.6	0.163(.686)
		>1day	7	10315	21.7	69	93820	17.4	
	Smoked in last 100days	No	72	108720	77.3	807	1147033	88.1	1.536(.215)
		Yes	28	31845	22.7	137	155520	11.9	
	Exercise any last 30days	No	31	35617	24.9	220	315868	24.3	0.006(.937)
		Yes	75	107642	75.1	720	983213	75.7	
	Fruit frequency/Day /Week	0	7	7081	15.5	65	93161	35.4	3.495(.062)
		>1Time/day	19	38458	84.5	110	169657	64.6	
	Green veg frequency	0	13	30668	67.3	110	175122	66.8	0.001(0.971)
		>1Time/day	13	14871	32.7	64	87083	33.2	
	Other veg Frequency	0	6	3970	8.7	59	90500	34.7	6.822(.009)
		>1Time/day	20	41569	91.3	1133	169980	65.3	

Multivariate Analysis

Using a hierarchical approach, the logistic regression analysis examined the determinants of T2DM in 3 blocks: sociodemographic factors, behavioral factors, and access to care factors. Within the socioeconomic factors, the logistic regression analysis showed that the statistically significant determinants for the diagnosis of T2DM to be age (X^2 = 3.40, p = <.001) and internet use (X^2 = -1.97, p = 0.049), as shown in Table 5. More specifically, the odds of being diagnosed with T2DM were 4 times higher among older AIs in comparison to younger adults (OR = 3.89, 95% CI: 1.78-8.52) and 68% lower with using the internet in comparison to not using the internet (OR = 0.32, 95% CI: 0.11-0.99).

Within the intermediary factors, the logistic regression analysis showed the statistically significant determinants for the diagnosis of T2DM to be having a personal doctor (X^2 = 0.84, p = .002), as shown in Table 6. More specifically, the odds of being diagnosed with T2DM were 5.3 times higher with having a personal doctor than with not having a personal doctor (OR =5.34, 95% CI: 1.84-15.50).

Table 5

Logistic regression analysis: SEP, Intermediary Variables, and T2DM

	Ever had a T2DM diagnosis							
	B	**SE**	**Wald**	**df**	**p**	**Exp(B)/ OR**	**95% Confidence interval**	
Demographic and SEP factors (N=867)								
Age (>44years vs. <44years)	0.68	0.20	3.40	827	<.001	3.89	1.78	8.52
Sex (Female vs. Male)	-0.20	0.18	-1.11	827	0.266	0.67	0.33	1.36
BMI (Obese/overweight vs. Normal/underweight)	0.24	0.17	1.37	827	0.170	1.62	0.81	3.21
Income (>/=75K/year vs. <75K/year)	-0.26	0.20	-1.27	827	0.204	0.60	0.27	1.32
Home ownership (Own vs. Rent)	-0.06	0.22	-0.28	827	0.781	0.88	0.37	2.11
Internet use (Yes vs. No)	-0.56	0.29	-1.97	827	0.049	0.32	0.11	0.99
Constant = 0.712								
Omnibus tests of model coefficients: *Chi-square(df), p-value* = 5.43(868), <.001								
Model summary: *-2 Log likelihood; R^2* = 659782.82; .161								
Behavioral factors (N=161)								
Alcohol intake last 30 days (Yes vs. No)	-0.55	0.30	-1.85	163	0.066	0.33	0.10	1.08
Smoked 100 cigarettes (Yes vs. No)	0.68	0.38	1.77	163	0.078	3.91	0.86	17.81
Fruit intake (Yes vs. No)	0.32	0.31	1.03	163	0.303	1.91	0.55	6.59
Vegetable intake (Yes vs. No)	0.63	0.37	1.71	163	0.089	3.54	0.82	15.21
Constant = 0.696								
Omnibus tests of model coefficients: *Chi-square(df), p-value* = 3.83(160), 0.005								
Model summary: *-2 Log likelihood**;** R^2* = 227485.84; .161								
Access to care factors (N=1,049)								
Check-ups in the last 2 years (Yes vs. No)	0.50	0.40	1.23	1049	0.219	2.70	0.56	13.11
Personal doctor (Yes vs. No)	0.84	0.27	3.09	1049	0.002	5.34	1.84	15.50
Constant = 0.592								
Omnibus tests of model coefficients: *Chi-square(df), p-value* = 6.11(1048), .002								
Model summary: *-2 Log likelihood; R^2* = 917408.10; .043								

Determinants of Prediabetes (PDM)

Bivariate Analysis

Bivariate analyses, using Chi-square, revealed that having a PDM diagnosis was statistically associated with age, sex, medical check-up, and having a personal doctor (Table 7). More specifically, having a PDM diagnosis was significantly higher among older AIs in comparison to the younger ones (X^2 = 17.8, p = <.001), and among males in comparison to females (X^2 = 4.45, p = .035. Having a PDM diagnosis was also significantly higher among AIs who reported having had their medical check-ups in comparison to those who did not have medical check-ups (X^2 = 9, p = .003) and those who have a personal doctor in comparison to those who do not have a personal doctor (X^2 = 5.52, p = .019).

Table 6

Associations Between Having a Prediabetes (PDM) Diagnosis, and Demographic, SEP, Access to Care, and Behavioral Variables (n=1,132).

Correlates		Outcome	Having a PDM diagnosis Raw n	Weight-ed n	Row %	Having No PDM diagnosis Raw n	Weight-ed n	Row%	X^2 (P)
Demographic and SEP variables	Age	18-44	29	32871	36.5	241	339256	70.2	17.803 (<.001)
		>44years	38	57252	63.5	110	143864	29.8	
	Sex	Male	45	59297	64.9	191	227383	46	4.450 (.035)
		Female	24	32046	35.1	171	266510	54	
	Marital Status	Not Married/living alone	14	16799	18.4	82	125502	25.7	1.016 (.314)
		Married living together	55	74544	81.6	274	363455	74.3	
	Income	<75K/year	20	23846	29.8	110	150925	37.3	.677 (.411)
		>/=75K/year	38	56188	70.2	181	253919	62.7	
	Education	Below high school	6	9625	10.5	40	80904	16.6	.995 (.319)
		High school/college	63	81717	89.5	316	405585	83.4	
	Employment	Not employed	19	20002	21.9	97	138858	28.7	0.879 (.348)
		Employed	50	71341	78.1	256	345440	71.3	
	Home ownership	Rent/other	45	70954	85	221	352011	73.6	3.349 (.067)
		Own	15	12501	15	127	126046	26.4	
	Internet	No	6	8047	8.8	18	20806	4.4	1.730 (.189)
		Yes	63	83296	91.2	325	457100	95.6	
Access to care variables	Health plan	No	3	3078	3.4	31	41377	8.4	2.200 (.138)
		Yes	66	88264	96.6	329	450159	91.6	
	Routine checkup in last 2 years	No	1	366.937	1	16	22870	4.8	9.000 (.003)
		Yes	67	89520	99.6	331	454804	95.2	
	Missed medical help due to cost	No	62	84212	92.4	322	428532	87.3	1.174 (.279)
		Yes	6	6975	7.6	37	62562	12.7	
	Personal Doctor	No	8	6514	7.1	78	86041	17.5	5.515 (.019)
		Yes	61	84829	92.9	280	404921	82.5	
Intermediary variables	BMI	Normal/under weight	13	16287	17.8	100	137864	27.9	2.022 (.155)
		Obese/overweight	56	75056	82.2	262	356029	72.1	
	Alcohol days in last 30 days	0	39	50715	55.8	184	260356	59.2	0.172 (.679)
		>1day	29	40214	44.2	130	179310	40.8	
	Binge drinking in last 30 days	0	26	36056	89.7	109	147965	82.9	0.658 (.417)
		>1day	3	4159	10.3	20	30499	17.1	
	Smoked in last 100days	No	60	82526	90.3	281	399065	87.7	0.308 (.579)
		Yes	9	8816	9.7	45	55752	12.3	
	Exercise any last 30days	No	14	20460	23.3	76	92471	19.9	0.213 (0.645)
		Yes	52	67208	76.7	263	371793	80.1	
	Fruit frequency/Day/Week	0	11	12125	31.6	49	74112	36.3	0.177 (.674)
		>1Time/day	18	26284	68.4	81	130125	63.7	
	Green veg frequency	0	17	21326	55.5	81	139806	68.7	1.166 (0.280)
		>1Time/day	12	17083	44.5	48	63817	31.3	
	Other veg Frequency	0	10	9825	25.6	44	73920	36.6	0.988 (.320)
		>1Time/day	19	28584	74.4	83	127979	63.4	

Multivariate Analyses

Using a hierarchical approach, the logistic regression analysis examined the determinants of PDM in 3 blocks: sociodemographic factors, behavioral factors, and access to care factors. Within the socioeconomic factors, the logistic regression analysis did not identify statistically significant determinants for the diagnosis of PDM, as shown in Table 8. Among demographic variables, age was a statistically significant determinant for PDM (X^2 = 3.39, p = <.001). More specifically, the odds of being diagnosed with PDM were 3.9 times higher for people who were more than 45 years (OR =3.94, 95% CI: 1.78 – 8.73).

Within the intermediary factors, the logistic regression analysis showed the statistically significant determinants for the diagnosis of PDM to be having medical check-ups (X^2 = 1.20, p = .030). More specifically, the odds of being diagnosed with PDM were 10.9 times higher among AIs who reported having at least one medical check-up in the last two years than those who reported having no medical check-ups in the last 2 years (OR =10.92, 95% CI: 1.27 - 94), as shown in Table 9.

Table 7

Logistic regression analysis: SEP, behavioral variables, access to care variables, and PDM

	Ever had prediabetes (PDM) diagnosis							
Determinants	**B**	**SE**	**Wald**	**df**	**p**	**Exp(B)/ OR**	**95% Confidence interval**	
Sociodemographic factors (N=336)								
Age (>44 years vs. <44 years)	0.69	0.20	3.39	339	<.001	3.94	1.78	8.73
Sex (Female vs. Male)	-0.38	0.21	-1.78	339	0.076	0.47	0.21	1.08
BMI (Obese/ overweight vs. Normal/underweight)	0.09	0.23	0.40	339	0.691	1.21	0.48	3.03
Home ownership (Own vs. Rent)	-0.16	0.21	-0.77	339	0.443	0.72	0.32	1.66
Internet (Yes vs. No)	-0.28	0.30	-0.92	339	0.358	0.57	0.17	1.88
Constant = 0.693								
Omnibus tests of model coefficients: *Chi-square(df), p-value* = 5.41(335); <.001								
Model summary: *-2 Log likelihood; R^2* = 409397.34; .154								
Behavioral factors (N=128)								
Green Vegetables (Yes vs. No)	0.2812	0.2617	1.070	127	0.2847	1.755	0.623	4.944
Constant = 0.521								
Omnibus tests of model coefficients: *Chi-square(df), p-value* = 1.15(127); .285								
Model summary: *-2 Log likelihood; R^2* = 209357.72; .017								
Access to care factors (N=364)								
Health Plan (Yes vs. No)	0.26	0.35	0.74	366	0.459	1.67	0.43	6.56
Checkup (Yes vs. No)	1.20	0.55	2.18	366	0.030	10.92	1.27	94.00
Missed care due to Medical Cost (Yes vs. No)	-0.40	0.29	-1.4	366	0.162	0.45	0.14	1.38
Personal Doctor (Yes vs. No)	0.78	0.47	1.67	366	0.096	2.19	0.87	5.49
Constant = 0.566								
Omnibus tests of model coefficients: *Chi-square(df), p-value* = 2.37(363); 0.052								
Model summary: *-2 Log likelihood; R^2* = 477915.47; .047								

Determinants of Diabetes Status (DS)

Bivariate Analysis

Bivariate analyses, using Chi-square, revealed that having a positive DS (having a diagnosis of either T2DM or PDM) was statistically associated with age, BMI, home ownership, internet use, medical check-ups having a personal doctor, and other vegetable intakes (Table 10). More specifically, having a positive DS was significantly higher among older AIs (X^2 = 39.24, p = <.001) and those with an obese/overweight BMI (X^2 = 8.72, p = .003). Positive DS was also significantly higher with no home ownership (X^2 = 6.24, p = .013) and use of the internet (X^2 = 10.47, p = .001). Moreover, positive DS was significantly increased with having a personal doctor (X^2 = 23.98, p = <.001) and medical check-ups and with vegetable intake (X^2 = 5.92, p = .015).

Table 8

Associations between having a diabetes status (DS), demographic, SEP, access to care, and behavioral variables (n=1,132).

	Correlates	Outcome	Having a DS diagnosis Raw n	Weight-ed n	Row%	Having no DS diagnosis Raw n	Weight-ed n	Row%	X^2 (P)
Demographic and SEP variables	Age	18-44	59	78933	33.2	638	881540	69	39.244
		>44years	117	158632	66.8	296	396957	31	(<.001)
	Sex	Male	123	146118	61.1	549	640051	49.4	3.592
		Female	56	93161	38.9	404	655107	50.6	(.058)
	Marital Status	Not Married/living alone	36	44029	18.4	200	297033	23	0.762 (.383)
		Married living together	141	194648	81.6	745	991661	77	
	Income	<75K/year	68	94256	46.4	299	410900	38.6	1.719
		>/=75K/year	88	108894	53.6	489	654426	61.4	(.190)
	Education	Below high school	20	36165	15.2	94	193880	15.1	0.001 (.981)
		High school/college	158	202065	84.8	852	1092854	84.9	
	Employment	Not employed	57	69166	29	235	354263	27.6	0.069
		Employed	120	169511	71	706	929161	72.4	(.792)
	Home ownership	Rent/other	122	180893	82.7	548	892070	72	6.235 (.013)
		Own	42	37732	17.3	362	403089	28	
	Internet	No	19	33578	14.4	51	61123	4.8	10.470
		Yes	151	199224	85.6	865	1199355	95.2	(.001)
Access to care variables	Health plan	No	12	16979	7.1	83	129060	9.4	0.442
		Yes	167	222300	92.9	865	1166099	90.6	(.506)
	Routine checkup in last 2 years	No	3	3796	1.6	72	102644	8.1	6.667
		Yes	171	230304	98.4	851	1162083	91.9	(.010)
	Missed medical help due to cost	No	156	214510	91.2	859	1165708	90.6	0.054
		Yes	19	20607	8.8	88	120765	9.4	(.816)
	Personal Doctor	No	15	13105	5.5	213	261128	20.3	23.979
		Yes	164	226174	94.5	733	1026801	79.7	(<.001)
Intermediary variables	BMI	Normal/under weight	44	45995	19.2	293	425654	32.9	8.720 (.003)
		Obese/overweight	135	193285	80.8	660	869505	67.1	
	Alcohol days in last 30 days	0	101	143716	62.1	471	674109	56.8	0.832
		>1day	67	87779	37.9	384	513064	43.2	(.362)
	Binge drinking in last 30 days	0	169	73305	83.5	311	1205497	82.1	0.034
		>1day	10	14474	16.5	66	89661	17.9	(.854)
	Smoked in last 100days	No	132	191246	82.5	747	1064506	87.9	1.758 (.185)
		Yes	37	40662	17.5	128	146704	12.1	
	Exercise any last 30days	No	45	56077	24.3	206	295408	24.4	0.000 (.985)
		Yes	127	174850	75.7	668	916005	75.6	
	Fruit frequency/Day/Week	0	18	19206	22.9	54	81036	36.1	2.321 (.128)
		>1Time/day	37	64742	77.1	92	143374	63.9	
	Green veg frequency	0	30	51994	61.9	93	153795	68.7	0.403 (.525)
		>1Time/day	25	31954	38.1	52	70000	31.3	
	Other veg Frequency	0	16	13794	16.4	49	80675	36.3	5.924 (.015)
		>1Time/day	39	70154	83.6	94	141396	63.7	

Hypotheses

Primary Hypothesis. AIs in NJ at a higher SEP (education/ occupation/income/homeownership/ internet use) will have a lower diagnosis of diabetes status compared to those who are at a lower SEP.

Multivariate Analysis of Diabetes Status (DS)

Using a hierarchical approach, the logistic regression analysis examined the Determinants of DS in 3 blocks: sociodemographic factors, behavioral factors, and access to care factors. Within the socioeconomic factors, the logistic regression analysis showed the statistically significant determinants for the diagnosis of DS to be internet use (X^2 = -0.54, p = .019), as shown in Table 11. More specifically, the odds of having a positive DS were 66% lower with the use of the internet than with not using the internet (OR =0.34, 95% CI: 0.14-0.84). Thus, the primary hypothesis was supported.

Table 9

Logistic regression analysis: SEP and DS

	Have diabetes status (DS)							
Determinants	**B**	**SE**	**Wald**	**df**	**p**	**Exp(B)/ OR**	**95% Confidence limits**	
Demographic and SEP factors (N=823)								
Age (>44 years vs. <44 years)	0.63	0.15	4.33	827	<.001	3.55	2.00	6.30
Sex (Female vs. Male)	-0.25	0.15	-1.69	827	0.092	0.61	0.34	1.09
BMI (Obese/overweight vs. Normal/underweight)	0.25	0.15	1.67	827	0.096	1.64	0.92	2.92
Income (>/=75K/year vs. <75K/year)	-0.07	0.16	-0.43	827	0.664	0.87	0.47	1.61
Home ownership (Own vs. Rent)	-0.14	0.17	-0.86	827	0.390	0.75	0.39	1.44
Internet (Yes vs. No)	-0.54	0.23	-2.34	827	0.019	0.34	0.14	0.84
Constant = 0.697								
Omnibus tests of model coefficients: *Chi-square(df), p-value* = 7.86 (822), <.001								
Model summary: *-2 Log likelihood;* R^2 = 918235.93; .162								

Exploratory Hypothesis 1. AIs in NJ who follow healthier behaviors (increased fruit and vegetable intake, decreased tobacco or alcohol consumption, and exercise) and have health care access (medical check-up, health plan, personal doctor, no missed health care due to medical cost) will have a lower diagnosis of DS compared to those who do not follow healthier behaviors and have no access to health care.

Within the behavioral factors, the logistic regression analysis showed no statistically significant determinants for having a positive DS. Within the access to care factors, the logistic regression analysis showed the statistically significant predictor for having a positive DS to be having medical check-ups (X^2 = 0.74, p = .043) and personal doctor (X^2 = -0.70, p = <.001), as shown in Table 12. More specifically, the odds of having a positive DS were 4 times higher for AIs who reported having had at least one medical checkup in two years than those who reported having no medical check-ups in the last two years (OR = 4.40, 95% CI, 1.05-18.48) and 4 times higher for those who have a personal doctor than those who have no personal doctor (OR = 4.03, 95% CI: 2.03-8.00). Thus, this hypothesis was not supported.

Table 10

Logistic Regression Analysis: Intermediary Variables and DS

	Ever had a diabetes status (DS) diagnosis							
Determinants	**B**	**SE**	**Wald**	**df**	**p**	**Exp(B)/ OR**	**95% Confidence limits**	
Behavioral factors (N=163)								
Smoked 100 cigarettes (Yes vs. No)	0.35	0.30	1.16	164	0.248	2.00	0.62	6.50
Fruit Intake (Yes vs. No)	0.17	0.22	0.77	164	0.440	1.41	0.59	3.35
Vegetable intake (Yes vs. No)	0.46	0.24	1.91	164	0.058	2.49	0.97	6.37
Constant = 0.581								
Omnibus Tests of Model Coefficients: *Chi-square(df), p-value* = 2.39 (162), 0.071								
Model Summary: *-2 Log likelihood**;** R^2* = 342900.69; .077								
Access to Care Factors (N=1,048)								
Checkup (Yes vs. No)	0.74	0.37	2.03	1049	0.043	4.40	1.05	18.48
Personal Doctor (Yes vs. No)	0.70	0.17	3.99	1049	<.001	4.03	2.03	8.00
Constant = 0.586								
Omnibus Tests of Model Coefficients: *Chi-square(df), p-value* = 10.84(1048), <.001								
Model Summary: *-2 Log likelihood; R^2* = 1249761.0; .053								

Exploratory Hypothesis 2. Healthier behaviors (increased fruit and vegetable intake/decreased tobacco and alcohol consumption/increased exercise) mediate the relationship between high SEP and the diagnosis of DS among AIs in NJ.

SEP may be linked with healthier behaviors in a certain subpopulation, however, the marginal association between the health-related behaviors and the diagnosis of DS was not detected as a significant effect in the regression analyses. Mediation is a possibility even when the association of health-related behavior and DS does not appear to be significant. However, the non-significant relationship between health-related behavior and DS may be due to a lack of adequate sample size for the behavioral variables. There were significantly low cross-tabulated cell sizes for some behavioral variables. Thus, it was decided to exclude mediation analysis for the second exploratory hypothesis. This hypothesis was not supported in this study.

Exploratory Hypothesis 3. Health care access mediates the relationship between SEP and the diagnosis of DS among AIs in NJ.

Mediation analysis-T2DM

Mediation analysis was conducted for T2DM and the results of mediation are summarized in Table 13 and Figure 5. The independent variable was the internet, the mediator variable was personal doctor, and the dependent variable was the diagnosis of T2DM. The total effect is to compare the odds of T2DM with and without internet use and shows the net effect of having internet on the diagnosis of T2DM. Summary effects showed a negative total effect (TE) i.e., the sum of the effect of the internet on the diagnosis of T2DM when the mediator personal doctor variable was held at the values corresponding to using the internet (OR = 0.353, 95% CI 0.347-0.360, p= <.001). In other words, having internet was associated with 65% decreased odds of T2DM.

The natural direct effect of the internet is to compare the change in the odds of T2DM when the internet is present and absent while holding the odds of having a personal doctor at the level of internet absence. There was a negative natural direct effect of the internet on T2DM when the pathway does not involve the mediator i.e., the value of personal doctor was set to the level of not using the internet (ORNDE = 0.324, 95% CI 0.317-0.330, p= <.001). In other words, using the internet decreased the odds of T2DM by 68% when the odds of having a personal doctor corresponds to not using the internet.

The controlled direct effect (CDE) of the internet is the effect of internet use on the diagnosis of T2DM when having a personal doctor was held absent. There was a negative controlled direct effect of the internet on T2DM when the personal doctor was absent (ORCDE = 0.324, 95% CI 0.318-0.330, p= <.001). In other words, using the internet decreased the odds of T2DM by 68% when there was no personal doctor. This is different from the natural direct effect where the personal doctor was held to the value corresponding to not using the internet. The results indicated that there was no or small if any interaction effect between using internet and having a personal doctor on T2DM since the odds ratios for NDE and CDE are the same.

The natural indirect effect is the mediating effect of having a personal doctor. The mediating effect of having a personal doctor is to compare the change in the odds of T2DM between the odds of having a personal doctor when internet use is present and absent. The summary effects showed a positive natural indirect effect (NIE) of the internet on the diagnosis of T2DM mediated by having a personal doctor (ORNIE = 1.093, 95% CI 1.090-1.097, p = <.001). In other words, having internet increased the odds of having T2DM through the mediating effect of personal doctor by 1.1 times, as having internet increased the odds of having a personal doctor which in turn increased the odds of T2DM. Compared to the counterfactual situation when having internet but without a personal doctor, having both internet and a personal doctor would increase the odds of T2DM by 1.1 times diagnoses of T2DM than those who used the internet and did not have a personal doctor. Using the internet increased the odds of having a personal doctor by 1.8 times (a in Figure 5) and having a personal doctor increased the odds of being diagnosed with T2DM by 4.8 times (b in Figure 5).

Since higher age was associated with lower internet use and higher income was associated with higher internet use in regression analysis, the confounding factors age and income were controlled for the mediation analysis. Apart from controlling for significant covariates, Variance Inflation Factors (VIF) were analyzed for all variables of the study and found that they were all less than two indicating no multicollinearity. Refer to Appendix 3 for more details.

During mediation analysis, various decompositions of the total effect were obtained including two-way and four-way decompositions. The four-way decomposition of total effect showed that fourteen percent of the variance in the relationship between internet use and T2DM was explained by the mediator ‘having a personal doctor’. The proportion of the total effect of internet use on T2DM was reduced by 14% when the person had a personal doctor. In other words, having a personal doctor mediated the relationship between internet use and the diagnosis of T2DM.

Table 11

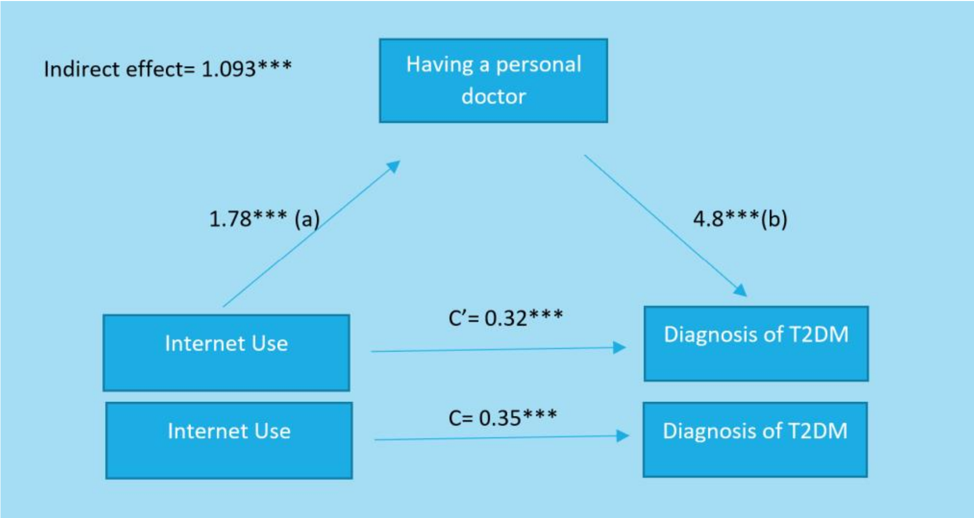
Mediation analysis between internet use, having a personal doctor, and T2DM using CAUSALMED procedure (n = 1,026)

OR	**Estimate**	**95% Confidence interval**		***p*-value**
Odds ratio total effect	0.3537	0.3470	0.3604	<.001
Odds ratio natural direct effect	0.3235	0.3174	0.3296	<.001
Odds ratio controlled direct effect	0.3235	0.3174	0.3296	<.001
Odds ratio natural indirect effect	1.0934	1.0897	1.0971	<.001

Note. Models were adjusted for age and income. The exposure was the internet, and the mediator was having a personal doctor.

Figure 5

Mediation analysis T2DM



Note. **p* < .05. ***p* < .01. ****p* < .001
C= Odds ratio total effect, C'=Odds ratio direct effect

Mediation analysis-PDM

Mediation analysis was conducted for PDM and the results of mediation are summarized in Table 14 and Figure 6. The independent variable was age, the mediator variable was having medical check-ups, and the outcome variable was the diagnosis of PDM. The total effect is to compare the odds of PDM when age less than or greater than 45 years and shows the net effect of age on the diagnosis of PDM. Summary effects showed a positive total effect (TE) i.e., the sum of the effect of age on the diagnosis of PDM when the mediator medical check-up variable is held at the value corresponding to age greater than 45years (OR = 3.515, 95% CI 3.459-3.570, *p*= <.001). In other words, age greater than 45 years was associated with 3.5 times increased odds of PDM. This is similar to the relationship established in regression analysis. The direct effect of age is to compare the change in the odds of PDM when age is less than 45 years and greater than 45 years while holding the odds of having medical check-ups at the level of age less than

45 years. There was a positive natural direct effect of age on PDM when the pathway does not involve the mediators i.e., the value of medical check-up is set to the value it would take when the age is less than 45 years (ORNDE = 3.436, 95% CI 3.382-3.491, *p*= <.001). In other words, age greater than 45 years increased the odds of PDM by 3.4 times when the odds of having medical check-ups corresponds to age less than 45 years.

The controlled direct effect (CDE) is the effect of age on the diagnosis of PDM when there was no more than one medical check-up. There was a positive controlled direct effect of age on PDM when the number of medical check-ups was not more than one in the last two years (ORCDE = 3.436, 95% CI 3.382-3.491, *p*= <.001). In other words, age greater than 45 years increased the odds of PDM 3.4 times when there was no more than one medical check-ups in last two years. The controlled direct effect is different from the natural direct effect where the number of medical check-ups was held to the value corresponding to age less than 45 years. The results indicated that there was no or small if any interaction effect between age and having more than two medical check-ups in last two years on PDM since the odds ratios for NDE and CDE are the same.

The natural indirect effect or the mediating effect of having medical check-ups is to compare the change in the odds of PDM between the odds of having medical check-ups when the age is greater than 45 years and when the age is less than 45 years. The summary effects showed a positive natural indirect effect (NIE) of age on the diagnosis of PDM mediated by having medical check-up (ORNIE = 1.023, 95% CI 1.022-1.024, *p* = <.001). In other words, age greater than 45 years increased the odds of having PDM through the mediating effect of medical check-ups by 1.02 times. This also means that among the participants greater than 45 years of age, there was more diagnosis of PDM independent of whether they had more than one medical check-up in the last two years even when having medical check-ups significantly increased the odds of having PDM. Moreover, age greater than 45 years increased the odds of having medical check-ups by 2 times (a in Figure 6) and having medical check-ups increased the odds of PDM by 9.3 times (b in Figure 6).

All relationships were statistically significant (p = <.001) in the two-way and four-way decompositions. The four-way decomposition of total effect showed that the proportion of the effect of age on the diagnosis of PDM was increased by 1% by having medical check-ups in the last two years. In other words, having medical check-ups mediated the relationship between age and diagnosis of PDM. Even though the effect is statistically significant, the mediating effect of medical check-ups on the relationship between age and the diagnosis of PDM may not be clinically significant.

Table 12

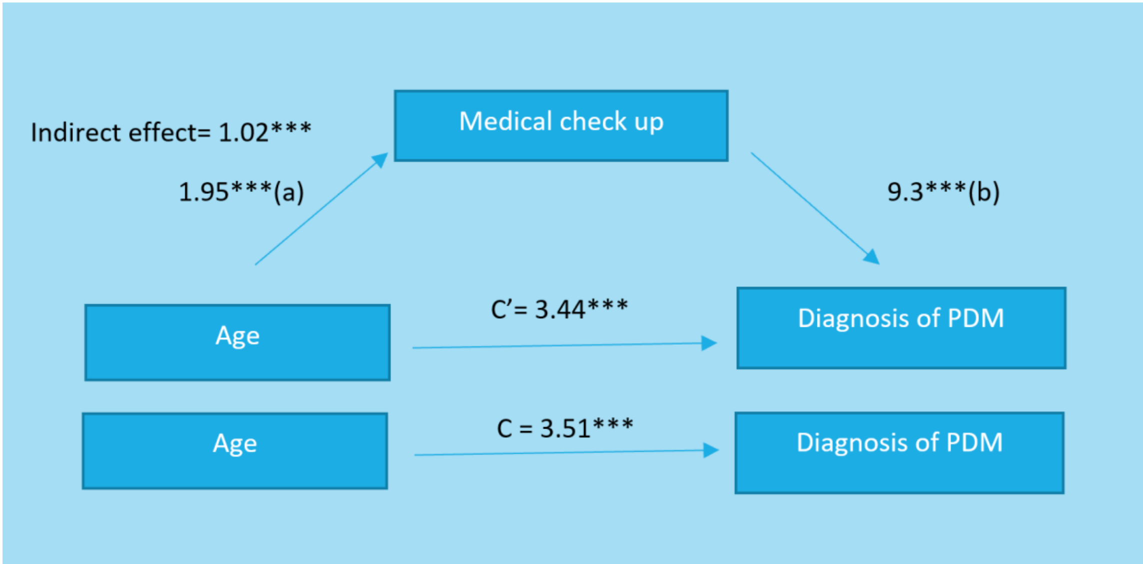
Mediation analysis between age, having medical check-ups, and prediabetes using CAUSALMED procedure (n = 393)

OR	**Estimate**	**95% Confidence interval**		***p*-value**
Odds ratio total effect	3.5145	3.4590	3.5701	<.001
Odds ratio natural direct effect	3.4364	3.3822	3.4906	<.001
Odds ratio controlled direct effect	3.4364	3.3822	3.4906	<.001
Odds ratio natural indirect effect	1.0227	1.0217	1.0237	<.001

Note. The exposure was the age, the mediator was having more than one medical check-up in the last 2 years, and the outcome was the diagnosis of PDM.

Figure 6

Mediation analysis PDM



Note. **p* < .05. ***p* < .01. ****p* < .001
C= Odds ratio total effect, C'=Odds ratio direct effect

Mediation analysis-DS

Mediation analysis was conducted for DS and the results of mediation are summarized in Table 15 and Figure 7. The total effect is to compare the odds of DS with and without internet use and shows the net effect of using the internet on the diagnosis of DS. Summary effects showed a negative total effect (TE) i.e., the sum of the effect of the internet on the diagnosis of DS when the mediator personal doctor was held at the values corresponding to using the internet (OR = 0.394, 95% CI 0.388-0.400, p= <.001). In other words, using the internet was associated with a 61% decreased odds of DS.

The direct effect of internet use is to compare the change in the odds of DS when the internet use is present and absent while holding the odds of having a personal doctor at the level of internet absence. There was a negative natural direct effect of the internet use on DS when the pathway does not involve the mediator i.e., the value of personal doctor was set to absent internet use (ORNDE = 0.375, 95% CI 0.369-0.381, *p*= <.001). In other words, having internet decreased the odds of DS by 63% when the odds of having a personal doctor corresponded to without internet use.

The controlled direct effect (CDE) is the effect of internet use on the diagnosis of DS when the personal doctor was held absent. There was a negative controlled direct effect of the internet use on DS when the value of personal doctor was held to absent (ORCDE = 0.375, 95% CI 0.369-0.381, *p*= <.001). In other words, having internet decreased the odds of DS by 63% when there was no personal doctor. The controlled direct effect is different from the natural direct effect where the personal doctor was held to the value corresponding to not using the internet. The results indicated that there was no or small if any interaction effect between using internet and having a personal doctor on DS since the odds ratios for NDE and CDE are the same.

The natural indirect effect is the mediating effect of having a personal doctor. The mediating effect of having a personal doctor is to compare the change in the odds of DS between the odds of having a personal doctor when internet use is present and absent. The summary effects showed a positive natural indirect effect (NIE) of the internet on the diagnosis of DS mediated by having a personal doctor (ORNIE = 1.050, 95% CI 1.048–1.054, *p* = <.001). In other words, having internet increased the odds of having DS through the mediating effect of personal doctor by 1.1 times. This also means that participants' odds of the diagnosis of DS were higher when they used the internet and had a personal doctor than when they used the internet without having a personal doctor.

The analysis also indicated that using the internet increased the odds of having a personal doctor by 1.8 times (a in Figure 7) and having a personal doctor increased the odds of DS by 4.8 times (b in Figure 7). Since higher age was associated with lower internet use and having medical check-ups was associated with having a personal doctor in regression analysis, the confounding factors age and medical check-ups were controlled for the mediation analysis. Thus, the results obtained were stratified for age and medical check-ups.

All relationships were statistically significant (p = <.001) in the two-way and four-way decompositions. The four-way decomposition of total effect showed that the proportion of the effect of internet use on DS was reduced by 8% by the mediator ‘having a personal doctor’. In other words, the effect of internet use on the diagnosis of DS among participants who used the internet was 8% lower if they had a personal doctor compared to those who did not have a personal doctor. Thus, having a personal doctor mediated the effect of internet use on the diagnosis of DS.

Table 13

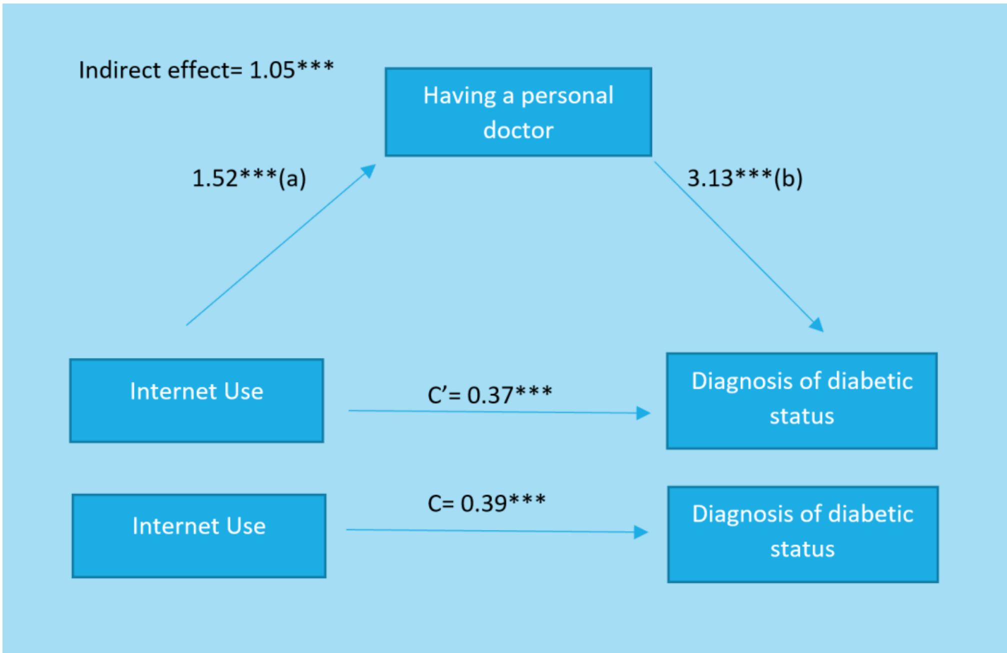
Mediation analysis between internet use, having a personal doctor, and diabetes status using CAUSALMED procedure (n = 1,026)

OR	**Estimate**	**95% Confidence interval**		***p*-value**
Odds ratio total effect	0.394	0.388	0.401	<.001
Odds ratio natural direct effect	0.375	0.369	0.381	<.001
Odds ratio controlled direct effect	0.375	0.369	0.381	<.001
Odds ratio natural indirect effect	1.050	1.048	1.053	<.001

Note. Models were adjusted for age and medical check-ups. The exposure variable was the internet, and the mediator was having a personal doctor.

Figure 7

Mediation Analysis DS



Note. *$p < .05$. **$p < .01$. ***$p < .001$
C= Odds ratio total effect, C'=Odds ratio direct effect

The mediation analysis results including the mediator and outcome models were statistically significant for T2DM, PDM, and DS. In conclusion, the third exploratory hypothesis of mediation was supported for T2DM, PDM, and DS. The proportion of the total effect of internet use on T2DM was reduced by 14% when the person had a personal doctor. The proportion of the effect of internet use on the diagnosis of DS among participants who used the internet was 8% lower if they had a personal doctor compared to those who did not have a personal doctor. However, the percentage of mediating effect (1%) of having medical check-ups on the relationship of age and the diagnosis of PDM may not be clinically significant even when it is statistically significant.

CHAPTER 5. DISCUSSION OF THE FINDINGS

The purpose of the study was to establish the relationship between structural and intermediary social determinants of health (SDH), and the diagnosis of type 2 diabetes mellitus (T2DM) and prediabetes (PDM) among Asian Indians (AIs) in New Jersey (NJ). Type 2 diabetes mellitus (T2DM) and prediabetes (PDM) were together termed as Diabetes Status (DS). The BRFSS data sets from the years 2013-2017 were combined and analyzed using SAS statistical software package. Four hypotheses derived from the theory guided the analysis of the relationships. The analyses tested the hypotheses of the study using Chi-square, logistic regression, and mediation analyses. The results and interpretations of each hypothesis testing will be discussed in detail in this chapter. The discussion will be based on the World Health Organization's (WHO) Conceptual framework for action on SDH (CSDH framework) of 2010.

Socioeconomic position (SEP) and Diabetes Status (DS)

The primary hypothesis of the study was AIs in NJ at a higher SEP (education/ occupation/income/homeownership/ internet use) will have a lower diagnosis of DS compared to those who are at a lower SEP.

This hypothesis was derived from the CSDH framework (Solar & Irwin, 2010), to explore the relationship between structural determinants of health and the outcome. The CSDH framework demonstrates SEP as part of structural SDH. The model posits a SEP and people's place in the social hierarchies lead to consistent inequalities in their exposure to health-compromising conditions (Solar & Irwin, 2010). The hypothesis was supported in this study among AIs in NJ for one component of SEP. The variable internet use had a significant negative relationship with the diagnosis of DS.

The relationship between the internet and the diagnosis of DS was significant in this study and remained consistent after adjusting for age, sex, BMI, and house ownership. The relationship was strong that the odds of being diagnosed with diabetes were 66% lower with internet use, a factor of higher SEP. Thus, this hypothesis was supported.

Some studies in the past have explored the possibilities of internet use in weight management, diabetes prevention, and diabetes management in other populations (Fagherazzi & Ravaud, 2019; Jara et al., 2011; McCoy et al., 2005). An internet-based weight loss program by using physical activity and dietary modifications was studied to reduce the risk for T2DM (McCoy et al., 2005). Many internet applications are useful in lifestyle modifications. Nowadays, internet and internet-based applications are widely available for use by the general public. However, there were no studies on this topic among AIs in the US. The results of this study were consistent with the other studies in the past about internet use in its positive impact on health by reducing diagnosis of DS.

The method by which internet use affects the diagnosis of DS requires further exploration among AIs in NJ. For example, whether the internet is used to obtain health-related knowledge, to choose the right health care providers, or to gain access to the applications for maintaining healthy lifestyles. There are numerous web-based applications tailored towards dietary management, promoting physical activities, and stress reduction. Many web-based applications are user-friendly and easily accessible through the internet and lots of them are free of cost. Web-based lifestyle modification programs have been demonstrated to be viable options in diabetic self-management and lifestyle modifications (Cotter et al., 2014; Jahangiry et al., 2014). All these can influence reducing the risk for DS.

On another note, internet use was not studied before as a correlate of higher SEP or T2DM among AIs. In regression analysis in this study, higher income was associated with higher internet use. Nowadays internet is available to almost every household and individual even to people of lower socioeconomic status. Thus, it was also important to learn how much the factor ‘internet use’ captures disparities in SEP in the AI population.

Similarly, a study among the Latina population in the US has also indicated that higher income and lower age were associated with higher internet use (Roncancio et al., 2012). The relationship between age and internet use among the Latina population was mediated by acculturation. Lower internet use to obtain health information among minority and the socioeconomically disadvantaged population was also indicated in secondary data analysis of the California Health Interview Survey (CHIS) conducted among multiple race/ethnicity groups in the US (Yoon et al., 2020). Similar relationship between age, income and internet use was indicated in other studies as well (Kruse et al., 2012; Mayben & Giordano, 2007)

The positive relationship between income and internet use in the previous studies was confirmed in this study. The AI participants who had a higher income used the internet more. Since the study indicates that the higher the internet use the lower the odds of being diagnosed with DS, AIs of low income who are not privileged to use the internet might have higher odds of being diagnosed with the DS. Hence, it is particularly important to provide low-income AIs with better internet access. Based on the findings of this study, improving access to the internet among underprivileged AIs could be a useful strategy to obtain health care information and reduce the odds of DS.

Among demographical variables in this study, age had an inverse relationship with internet use. Higher the age lower was the internet use among the AIs in the study. This is consistent with the findings of the previous studies on this topic (Kruse et al., 2012; Mayben & Giordano, 2007; Roncancio et al., 2012; Yoon et al., 2020). Computer literacy may be lower among the older population leading to less internet use. Increasing computer literacy, improving internet access, and mitigating other barriers to internet use among the older AI population might be effective tools in this population to implement health-related knowledge promotion and diabetes prevention strategies.

Other independent variables such as income, occupation, and education did not show any significant relationship with the diagnosis of DS in this study although these variables are consistently studied in literature as the proxy indicators of SEP (Agrawal & Ebrahim, 2012; Boddula et al., 2008; Gujral et al., 2015; Gupta et al., 2012).
Previous studies have shown relationships between education, family income, and T2DM prevalence among AIs. However, the relationships were inconsistent. While two studies mentioned a positive relationship between income level and diagnosis of T2DM among AIs in the US (Gujral et al., 2015; R. Misra et al., 2018), two studies mentioned no relationship (Gupta et al., 2012; Kanaya et al., 2014), and yet another study showed a curvilinear relationship (Nguyen et al., 2014) between family income and DS prevalence among AIs in the US.

The results of this study may be indicative of a lack of a consistent relationship between SEP factors such as income, occupation, and education and the diagnosis of DS among AIs in NJ. This could also be attributed to the homogeneity of the sample since the majority of the sample was educated, employed, and had a higher income level. However, SEP variables in this study had an adequate sample size to detect relationships. The crosstabulation cell sizes were all above 50 for the SEP variables, which is the required level to maintain the power of the study.

Healthier Behaviors, Access to Health Care, and Diabetes Status (DS)

The first exploratory hypothesis of the study was that AIs in NJ who follow healthier behaviors (increased fruit and vegetable intake, decreased tobacco or alcohol consumption, and exercise) and have health care access (medical check-up, health plan, personal doctor, no missed health care due to medical cost) will have a lower diagnosis of DS compared to those who do not follow healthier behaviors and have no access to health care.

This hypothesis was derived from the CSDH framework (Solar & Irwin, 2010), which explains health behaviors and health care access factors as intermediary determinants. The framework posits that intermediary determinants are the result of structural SDH, and they influence health outcomes (Solar & Irwin, 2010). There is substantial evidence in the literature that healthier behaviors are associated with diabetes among the AI population (Ghai et al., 2012; Kanaya et al., 2014; R. Misra et al., 2018; Mukherjea et al., 2013; Ram et al., 2014).

Among the behavioral variables examined in this study, vegetable intake, fruit intake, smoking, and alcohol consumption showed statistically significant relationships with the diagnosis of DS in the Chi-square analyses. Previous studies have shown that lower physical activity and higher carbohydrate intake were associated with higher T2DM among AIs in the US (Kanaya et al., 2014; A. Misra et al., 2018). Two studies indicated that lower fruit and vegetable intake was related to a lower incidence of T2DM among AIs in the US (Ghai et al., 2012; A. Misra et al., 2018; Ram et al., 2014). This is conflicting with some studies among AIs as well as studies in other populations. However, none of the behavioral factors remained significant in the logistic regression analysis in this study. This could be because these variables had a dramatic proportion of missing data. Cross-tabulated cell sizes of unweighted numbers should ideally be greater than 50 for accurate analyses. However, the significant drop in cell sizes of behavioral variables might have caused type ll error resulting in less accurate outcomes for the analyses and negatively impacting the power of the study. This study included five years of data to obtain a larger sample size. In the future, researchers could include the data from more states or obtain a national sample to procure an adequate sample size for this kind of analysis.

Moreover, some inadequacies of the BRFSS survey tool could have affected the accuracy of the data in the context of the AI culture. For instance, vegetable intake is measured in frequency, rather than in the amount of intake. Even when the AIs include vegetables in their diet, the portion size of vegetables in the diet may still be too low which may not be picked up by the BRFSS survey tool and the binary categories utilized in the analyses. Another limitation of the BRFSS survey report is that it is a self-reported survey and thus subject to social desirability and subject recall bias. A similar critique was raised by other researchers (Anderson & Marcum, 2019; Moore et al., 2015) about the BRFSS tool. Previous studies also have indicated that the dietary scales in BRFSS could be improved to obtain more data to inform the diet management programs (Fang et al., 2010; Moore et al., 2015).

Access to health care services is an essential contributor to health outcomes as per the CSDH framework (Solar & Irwin, 2010). The framework demonstrates equitable access to care can address the exposure and vulnerability to inequity in care issues in health. A proper health system can also achieve health promotion and disease prevention (Angel González Block et al., 2001). More than one medical check-ups in the last two years and having a personal doctor were the access to care variables that were significantly related to the diagnosis of DS in this study. Both variables in this study were associated with a significantly higher prevalence of DS.

The mechanism underlying this result could be individuals getting diagnosed at a higher rate through regular check-ups while those who do not have regular check-ups may remain undiagnosed even if they have positive DS (Zhang & Tsai, 2014). Those who have a personal doctor must also have regular medical check-ups and detect the DS earlier than those who do not have a personal doctor. Thus, even when the access to care factors was associated with a higher diagnosis of DS, these factors prevent undiagnosed cases, lead to early diagnosis and treatment of the DS.

Again, these relationships cannot imply causation since the temporality of the events is not established in a cross-sectional study. In other words, people with the diagnosis of DS might have opted for having a personal doctor due to the diagnosis than those who do not have the diagnosis of DS. Or people who have DS tend to get more medical check-ups to monitor blood sugar levels. Also, the access to care factor having a personal doctor could have caused DS to be diagnosed more. A longitudinal study is essential to understand the temporal factors in this relationship. In conclusion, this hypothesis was not supported for behavioral factors, and a reverse effect was noticed for the access to care factors.

SEP, Health-Related Behaviors, and Diabetes Status (DS)

The second exploratory hypothesis was that healthier behaviors (increased fruit and vegetable intake/decreased tobacco and alcohol consumption/increased physical activity) mediate the relationship between SEP and the diagnosis of DS among AIs in NJ.

The CSDH framework demonstrates how healthier behaviors can be triggered by socioeconomic conditions. The socioeconomic conditions in turn influence the vulnerability of the individual to have an unfavorable health outcome (Solar & Irwin, 2010). Healthier behaviors were not linked to the diagnosis of DS in the regression analysis of this study, and this could be attributed to the lack of adequate sample size of the variables included. Reduced sample size affected the power of the study due to the significant reduction in cross-tabulation cell sizes of behavioral variables as discussed before in this chapter. For this reason, the mediation analysis was not conducted to analyze this relationship. No studies were found analyzing this mediating role of healthier behaviors between SEP and T2DM prevalence among AIs in the US. Future studies could explore this relationship with adequate sample size to maintain the required cross-tabulation cell sizes.

SEP, Access to Health Care, and Diabetes Status (DS)

The third exploratory hypothesis was that health care access mediates the relationship between SEP and the diagnosis of DS among AIs in NJ.

This hypothesis was derived from the presentation of health care access as an accessory pathway between the structural SDH and health care outcome in the CSDH framework. The CSDH framework posits that the health system is a factor resulting from the structural SDH factors and the health system plays a determining role in an individual's health status (Solar & Irwin, 2010). Health systems are relevant because of the issue of health care access. Health system and access to health care factors impact an individual's health in various ways such as reducing susceptibility to illness (e.g. by obtaining vaccinations), promoting treatment and rehabilitation, surveillance and monitoring for early detection of illness, and protecting against social and economic consequences of diseases (Diderichsen F & Hallqvist J, 1998).

It has been studied that health care access alone cannot explain the relationship between SEP and health status (Adler et al., 1994). However, the CSDH framework considers that health system factors are indirect determinants of health inequities. The framework also states that health care access factors decide the movement of people up and down in social stratification, and the differences in exposure and vulnerability to illness (Solar & Irwin, 2010).

This hypothesis was supported in this study. The SEP factor included in the mediation analysis was internet use, access to care factor was having a personal doctor for the outcome variable T2DM. The four-way decomposition in mediation analysis showed that 14% of the variance in the relationship between internet use and the diagnosis of T2DM was explained by having a personal doctor. This is after adjusting for the confounding factors of age and income for T2DM. After stratified on age and income through its interaction with internet use, having a personal doctor for people who used the internet resulted in a decrease in the negative effect of internet use on the odds of T2DM.

Regression analysis indicated that people who used the internet had 68% lower odds of T2DM compared to people who did not use the internet. This relationship remained consistent in the mediation analysis with a value of 65%. People who used the internet might have more access to information on preventive care. The positive influence of health care knowledge and health-related behaviors adopted through the internet might have influenced lowering incidence or delaying the onset of T2DM. Some studies in the past have noted the impact of internet-based applications on developing and maintaining healthier lifestyles (Cotter et al., 2014; Jahangiry et al., 2014; McCoy et al., 2005). The effect of internet use on reducing the odds of T2DM was consistent in mediation analysis. However, having a personal doctor increased the odds of T2DM even for people using the internet. These interpretations should be considered for further exploration by conducting focused studies.

In regression analysis, people who had a personal doctor had 5.3 times increased odds of T2DM compared to the people who did not have a personal doctor. Mediation analysis indicated the same relationship with 4.8 times increases in odds of T2DM by having a personal doctor. The results of mediation analysis had a much lesser standard error and a narrower confidence interval. The increase in odds of a diagnosis of T2DM with having a personal doctor could be attributed to the early detection of T2DM by the personal doctor or to the reverse causation of having a personal doctor after getting diagnosed with T2DM. The positive relationship between proper screening by the health care provider and the early diagnosis of diabetes is evident in the literature (Cowie, 2019). Based on scientific evidence, the latest screening recommendation by US preventive task force also is to screen for PDM and T2DM for adults 35-70 years old who have overweight or obesity ("Announcement: Community Preventive Services Task Force Recommendation for Team-Based Care for Patients with Type 2 Diabetes," 2017).

When people who used the internet also had a personal doctor, the negative effect of internet use on the diagnosis of T2DM was decreased because of the positive effect of having a personal doctor on the diagnosis of T2DM. In other words, there was a higher diagnosis of T2DM for people who used the internet when they also had a personal doctor than when they did not have a personal doctor. This is after adjusting for age and income. The results indicated that there was no or small if any interaction effect between using internet and having a personal doctor on T2DM.

This information points to the importance of the internet in reducing the diagnosis of T2DM and also the role of having a personal doctor on timely diagnosis of the T2DM among AIs in NJ. Studies in the past have indicated the use of the internet for acquiring health-related information (Kruse et al., 2012; Mayben & Giordano, 2007; Roncancio et al., 2012). The public health efforts among AIs in NJ should focus on reaching out to the unprivileged who do not have internet access to improve access to the internet or to provide health-related information via multiple other avenues.

Preventive care for AIs should also address those who do not have personal doctors to provide opportunities for testing and early detection of T2DM. Providing additional testing options through non-profit organizations by providing them incentives should be considered among AIs. Using urgent care services for diabetes testing also has been studied in the past as an option to improve screening and early detection of DS (Clark & Wilson, 2016).

For PDM, age and medical check-up variables were included in the mediation analysis. The mediation analysis showed 1% of the variance in the relationship between age and prediabetes was explained by the mediator medical check-up. This finding may mean that the increased diagnosis of PDM among AIs at a higher age may be related to the fact that people at older age get more frequent medical check-ups and hence diagnosed with PDM at a higher rate than people at a lower age. Even though this finding was statistically significant, this result may not be significant clinically since only 1% of the variance in the relationship between age and being diagnosed with PDM was explained by the mediator medical check-up.

Regression analysis showed that the odds of being diagnosed with PDM were 3.9 times higher for people who were more than 45 years of age. Similarly, in mediation analysis, age greater than 45 years was associated with 3.5 times increased odds of PDM. This relationship of age to the higher diagnosis of PDM is comparable to the other populations and emphasizes the importance of specifically addressing the older AI population in preventive efforts for PDM.

The odds of being diagnosed with PDM were 10.9 times higher among AIs who reported having at least one medical check-up in the last two years than those who reported having no medical check-ups in the last 2 years. Similarly, in mediation analysis having medical check-ups increased the odds of being diagnosed with PDM by 9.3 times. The consistent relationship of having medical check-ups and diagnosis of PDM highlights the significance of testing in the early detection of PDM among AIs. The results of mediation analysis had a much lesser standard error and a narrower confidence interval. The mediation effect of having medical check-ups in the relationship between age and higher diagnosis of PDM may not be clinically significant even though statistically significant because age had a positive relationship with the diagnosis of PDM regardless of the number of medical check-ups. The results indicated that there was no or small if any interaction effect between age and medical check-ups on PDM.

This hypothesis was supported for DS as well. The SEP factor included in the mediation analysis was internet use and the access to care factor was having a personal doctor for DS. Age and more than one medical check-up in the past 2 years were the confounding variables that were controlled in the mediation analysis. The four-way decomposition in mediation analysis showed that 8% of the variance in the relationship between internet use and the diagnosis of DS was explained by having a personal doctor after adjusting for age and income. More specifically, after stratified on age and income through its interaction with internet use, having a personal doctor for people who used the internet resulted in reduced effect of internet use on lessening the odds of DS.

Regression analysis indicated that people who used the internet had 66% lower odds of DS compared to people who did not use the internet. This relationship remained consistent in the mediation analysis with a value of 63%. The same factors mentioned previously in this section about the effect of internet use on the higher rate of diagnosis of T2DM are applicable here as well. In regression analysis, people who had a personal doctor had 4 times increased odds of DS compared to the people who did not have a personal doctor. Mediation analysis indicated the same relationship with 4.8 times increases in odds of DS by having a personal doctor. The results of mediation analysis had a much lesser standard error and a narrower confidence interval.

After adjusting for age, the internet's direct effect was to lower the odds of a diagnosis of DS, its indirect effect through a personal doctor was to increase the odds of DS. Mediation analysis revealed a change in the relationship between internet use on the diagnosis of DS when having a personal doctor was the mediator. People who used the internet had higher odds of being diagnosed with DS when they had a personal doctor than when they did not have a personal doctor. Reverse causation is a possible factor here because those who have DS are more likely to have a personal doctor. Also, those who have a personal doctor get diagnosed earlier due to timely medical check-ups. The relationship of having a personal doctor to the higher diagnosis of DS could be attributed to the early detection of DS or to the reverse causation of having a personal doctor after being diagnosed with DS. The results indicated that there was no or small if any interaction effect between using internet and having a personal doctor on DS.

Access to information on preventive care, and web-based applications assisting to make lifestyle modifications might have been the factors that influenced the reduction of the odds of DS Among AIs in NJ by using the internet (Cotter et al., 2014; Jahangiry et al., 2014; McCoy et al., 2005). Increased odds of a diagnosis of DS when having a personal doctor could be due to personal doctors detecting DS during medical check-ups or by lab studies. This could also imply that AIs who are not privileged to have a personal doctor are at high risk for delayed diagnosis of DS or maybe undiagnosed as evident in the literature (Cowie, 2019). This again points to the significance of public health activities and preventive care to be focused on the underprivileged AI population who do not have access to the internet and those who do not have a personal doctor.

Even if the mediation hypothesis was supported, there are temporal conditions that the data must satisfy so that the effects of the independent variable (IV) on the outcome, the IV on the mediator, and the mediator on the outcome can be observed. Conducting longitudinal studies is the better approach to establishing the causal sequence. Only a phased or staged data collection process ensuring a proper temporal ordering of the causal, mediation, and outcome events can effectively explain causation.

CHAPTER 6. SUMMARY, CONCLUSIONS, IMPLICATIONS, AND RECOMMENDATIONS

Summary

The purpose of the study was to examine the relationships between structural social determinants of health (SDH), intermediary determinants, and the diagnosis of type 2 diabetes mellitus (T2DM) and prediabetes (PDM) among Asian Indians (AI) in New Jersey (NJ). T2DM and PDM together are referred to as Diabetic Status (DS). According to World Health Organization (WHO), SDH is defined as the conditions in which people are born, grow, work, live, and age, and the wider set of forces and systems shaping the conditions of daily life (Solar & Irwin, 2010). The Conceptual Framework for Action on Social Determinants of Health (CSDH framework) by WHO provided the theoretical underpinnings of this study.

This study was a secondary data analysis of the Behavioral Risk Factors Surveillance System (BRFSS) survey of the state of New Jersey (NJ), during the years of 2013-2017. This was a quantitative study with a cross-sectional study design. The survey participants were adults greater than 18 years of age. This study focused on participants who were self-identified as Asian Indians (AI). The sample consisted of 1132 AIs living in NJ. BRFSS is a telephone survey conducted every year in the US. Studies have verified the reliability and validity of the BRFSS survey instrument (Newschaffer & Counte, 1998; Pierannunzi et al., 2013). The survey was conducted by trained professionals using a consistent and systematic approach. The BRFSS data of the state of NJ from the year 2013-2017 was obtained from the New Jersey Department of Health

(NJDOH) after IRB approval from Rowan University. The study also received IRB approval from Rutgers IRB.

The CSDH framework explains that a person's socioeconomic position (SEP), which is part of structural SDH is determined by factors such as income, occupation, education, gender, race, and ethnicity which in turn affects their health outcomes through the path of intermediary determinants such as behavioral factors and health system (Solar & Irwin, 2010). The demographic variables in this study included age, sex, and marital status. The SEP variables included in this study were income, education, occupation, homeownership, and internet use. The intermediary variables were behavioral (fruit intake, green vegetable intake, other vegetable intakes, exercise, alcohol use, and smoked in the last 100 days) and the access to health care variables (health plan, medical check-up in the last 2 years, missing care due to medical cost, and personal doctor). The SEP variables were the independent variables in this study. The intermediary variables were examined as mediators. The outcome variables were the diagnosis of T2DM, PDM, and DS. Demographic variables were included in the study as confounders.

The BRFSS data from the years 2013 to 2017 were combined using the Microsoft Access software program for analyzing the relationships. SAS statistical software package version 9.4 was used to conduct the analyses. A power analysis was conducted to ensure an adequate sample size for the study. The study was projected to have 80% power and the alpha value was set to 0.05. Proper weighing of the data was incorporated in the study so that the study results be representative of AIs in NJ.

The statistical procedures used for data analyses were descriptive analysis of the sample, Chi-square, crosstabulations, series of logistic regression analyses, and mediation analysis. The descriptive analyses used PROC SURVEYFREQ tool SAS to find frequencies, weighted frequencies, and percentages of the variables. Chi-square and crosstabulations were also conducted using PROC SURVEYFREQ to examine the relationship between the independent variables and the outcome variable. The PROC SURVEYLOGISTIC tool was used to conduct the logistic regression analyses. The regression analyses were conducted to find the best fitting model with the variables that had relationships with a *p*-value less than 0.3 in the Chi-square analyses. The PROC CAUSALMED tool was used to conduct mediation analyses to examine if the intermediary variables mediated the relationship between the structural and the outcome variables. The theoretical relationships developed in the study will be discussed under four hypotheses.

Primary Hypothesis: The primary hypothesis of the study was AIs in NJ at a higher SEP (education/ occupation/income/house ownership/ internet) will have a lower diagnosis of DS. Upon analysis, the results showed a significant relationship between the SEP factor internet use and the diagnosis of T2DM. The odds of being diagnosed with T2DM were 66% lower with having internet. This result could be attributed to using the internet to obtain health-related information or to access proper health care. Internet use for obtaining health-related information has been studied in the past in several populations. The results of this study were consistent with the relationships of age, income, and internet use that were established in the previous studies (Kruse et al., 2012; Roncancio et al., 2012; Yoon et al., 2020). Higher age and lower income were associated with lower internet use.

Exploratory Hypothesis 1: The first exploratory hypothesis of the study was AIs in NJ who follow healthier behaviors (increased fruit and vegetable intake, decreased tobacco or alcohol consumption, and increased physical activity) and have health care access (medical check-up, health plan, personal doctor, and medical cost) will have a lower diagnosis of DS. This hypothesis was not supported. Even though multiple intermediary factors had a significant relationship with the diagnosis of DS during Chi-square analysis, the only factor consistently remained significant after regression analysis was the personal doctor. Having a personal doctor increased the odds of being diagnosed with T2DM. This relationship is opposite to what was hypothesized. Temporalities of the events are a factor to be explored. None of the behavioral factors were found to have a significant relationship with the diagnosis of DS. The methodological concern for this non-significant relationship of behavioral factors to the diagnosis of T2DM is that the smaller crosstabulation cell sizes for the behavioral variables and that the instrument was not modified to use in the AI population.

Exploratory Hypothesis 2: The second exploratory hypothesis stated healthier behaviors (increased fruit and vegetable intake, decreased tobacco or alcohol consumption, and increased physical activity) mediate the relationship between high SEP and the diagnosis of DS among AIs in NJ. This hypothesis was not tested using mediation analysis since exploratory hypothesis 1 was not significant for behavioral factors and the cross-tabulated cell sizes were extremely low for some of the behavioral variables hindering accurate outcomes. The concern might be linked to the power of the study.

Exploratory Hypothesis 3: The third exploratory hypothesis was that health care access mediates the relationship between high SEP and the diagnosis of DS among AIs in the NJ. This hypothesis was supported for T2DM, PDM, and DS. Mediation analysis showed that 23% of the variance in the relationship between internet use and the diagnosis of T2DM was explained by having a personal doctor after stratified on age through its interaction with internet use. The mediation analysis showed 1% of the variance in the relationship between age and PDM was explained by the mediator medical check-up. After stratified on age through its interaction with internet use, 8% of the variance in the relationship between internet use and the diagnosis of DS was explained by having a personal doctor. Among the SEP variables, income, education, employment, homeownership, and internet use, internet use alone showed a positive relationship with the diagnosis of T2DM in this study. Even though multiple studies in the past have noted that the SEP levels and culture influenced health-related behaviors among AIs (Gupta et al., 2012; Kooner et al., 2011; Mehrotra et al., 2012; Nguyen et al., 2014), those findings were not consistent in the direction of the relationship. This study did not find any significant relationship between SEP and health-related behaviors that impacted the diagnosis of T2DM. Interestingly, BMI and health-related behaviors were not associated with the diagnosis of T2DM either after adjusting for covariates. However, SEP and access to care factors showed a significant relationship with the diagnosis of T2DM. Genetic, nativity, acculturation, and stress factors were not addressed in this study.

Limitations

Even with best efforts, this study comes with many limitations. Primarily, cross-sectional studies analyze the exposure and outcomes at the same point in time. Thus, the temporal relationship of exposure and disease cannot be determined in cross-sectional studies. For this reason, the associations indicated in this study cannot imply causation.

This study was a secondary analysis of the BRFSS survey results. One of the limitations of the study is that the BRFSS survey tool was a general survey not specifically developed for or studied in the AI population in the US to assess the SDH contributors of T2DM. A tool constructed to assess this research topic that is tested for reliability and validity in the AI population will provide more meaningful data. In the future researchers should try to use the tools that are developed for and tested in AIs in the US. Modifying the BRFSS tool appropriately, testing the tool among the AI population in the US, and conducting a primary study on this topic are also recommended.

Apart from this, the exposure and outcome variables were transformed to binary variables in this study. Yes or no answers for variables such as internet use, exercise, and vegetable intake might not provide adequate information on all important aspects of the variable. For example, yes or no answer to the internet use does not provide information on the frequency of use or the websites they use to understand how it affects the DS of the individual. Including the different aspects of internet use in the questionnaire could yield more meaningful results in future research.

Furthermore, using the data for AIs in NJ will not provide nationally representative results. However, weighing the data has maintained the representativeness of the sample to the AIs living in NJ. This is significant because the state of NJ is ranked third nationally in the total number of AI population. Furthermore, excluding participants with the age of onset of T2DM before 18 years of age can inadvertently exclude the teenage participants with T2DM due to obesity or other factors. These aspects limit the generalizability of the study findings to populations with similar characteristics to the study sample.

According to the CDC, the unweighted sizes should be larger than 50 for the denominator of the category (CDC, 2018). Even when the overall sample size met the calculated number, many of the cross-tabulation cell sizes were below 50 in this study. This could have increased the chance of type ll error leading to a lack of power for many of the analyses conducted.

The small, unweighted numbers could have resulted in unstable estimates, thus affecting the validity of the study design. This might have failed to capture the associations that could be existing in the real world. For example, a reduced sample size with the health-related behavior variables could have influenced the absence of the well-known relationship between the health-related behaviors and diagnosis of DS in this study. Another consideration was that the AI sample in the data set was less heterogeneous for the variables of the socioeconomic, behavioral, and access to care factors which significantly reduced some cell sizes in crosstabulations. The majority of participants in this study were educated, employed, and had higher income levels reducing the diversity of the sample. Acquiring a more heterogeneous sample and procuring a larger sample size is recommended for future studies. Expanding the data to multiple years or multiple states are options to consider.

Furthermore, the survey was self-reported. The validity of self-reported surveys can be affected by social desirability bias. This is particularly true with regards to health behaviors such as dietary patterns and physical activity. Moreover, the confounding factors of acculturation, nativity, genetics, and stress were not addressed in this study. For example, it could be expected that survey responses might differ among first, second, and third-generation AI immigrants. In addition to this, 18% of the sample did not have a personal doctor. Since the individuals are alerted about T2DM by the personal doctor, there may be more people in this data who might have T2DM or PDM and are not aware of their diagnosis. Finally, because the data presented in this study were collected from 2013 to 2017, caution must be exercised while extrapolating the findings to the present.

The sample size issues combined with the measurement reliability issues might have increased the chances of type ll error in this study. This would explain why some of the correlate variables that were thought to have an impact on the diagnosis of DS were not found significant in this study. Combining the data sets from more years or adding the data from neighboring states can help combat the sample size issues in future studies.

Implications for Nursing

With a ten-fold increase in T2DM prevalence over the last two decades, AIs have the higher age-adjusted prevalence of T2DM (12.6%) than all other Asian minorities, Blacks, Hispanics, and Whites as per the 2020 statistics (Department of Health and Human Services, 2020). The number of AIs in the US is on an upsurge (Batalova & Zong, 2017). Nurses especially in the tri-state area (New Jersey, New York, and Pennsylvania) are frequently taking care of AI patients. Culturally tailored nursing care is an essential part of health care. For these reasons, these study findings are essential to guide the nurses and practitioners caring for AIs in NJ.

Clinical Implications

The new knowledge that emerged from this study includes the significant relationships of having internet, and a personal doctor as well as the non-significance of the behavioral factors and BMI in the diagnosis of T2DM among AIs. This study reinforced the previous finding of the non-significance of BMI with the diagnosis of T2DM which places AIs at risk for developing T2DM even without an elevated BMI. Understanding the significant high risk for AIs to develop DS regardless of their healthier habits and low BMI is important for nurses and clinicians to plan preventive care for AIs. It is also important for clinicians to be aware that there is a higher prevalence of PDM than T2DM among AIs (Anjana et al., 2015; Kanaya et al., 2010).

Knowledge of the prevalence of PDM among AIs could be advantageous, in terms of the ability to either prevent or delay the onset of T2DM among this population. This study points to the importance of having a personal doctor and medical check-ups in the diagnosis of DS among AIs. Clinicians should be informed about the need for early diabetes screening for AIs. Awareness about the positive influence of internet use in reducing the diagnosis of diabetes among AIs can be important for clinicians who work in public health. Clinicians should also be informed to leverage the immense possibilities of technological advancement into preventive patient care and promoting self-management among AIs at risk for T2DM.

Individualizing the plan of care is critical in preventing or delaying the onset of T2DM among AIs. Recent pandemic also highlighted the significance of preventing T2DM and reducing obesity because both these factors increase the adverse outcomes and mortality risk of Covid-19 and make the management more complicated (Shivane et al., 2020). The relationship of higher internet use with lower odds of DS and the relationship of having a personal doctor with higher odds of DS also points to the significance of focused preventive care for the unprivileged and underprivileged AI population in NJ who do not have access to internet use or a personal doctor. The relationships established in this research will inform nurses and practitioners seeking ways to improve preventive care for the AIs by tailoring their health care action plans to the needs of the AI population.

Policy Implications

In the context of the growing number of AIs in the US and the pathological and financial implications of T2DM, it is essential to implement public health programs to prevent or delay the onset of T2DM within the AI population and reduce complications of T2DM and early death. Higher prevalence of PDM, the role of the internet and personal doctor in the diagnosis of DS in AIs, and the non-significance of BMI and behavioral factors with the diagnosis of DS are significant aspects of care this study brings up for consideration while creating health care policies impacting AIs. Despite the high risk of AIs being diagnosed with T2DM regardless of their BMI and health-related behaviors, the high proportion of increased BMI among AIs also necessitates careful attention by policymakers when planning and implementing preventive care for the AIs. Public health efforts should also focus on reducing obesity among the AI population in NJ since obesity is linked to many chronic health conditions including diabetes.

This study reports the significance of internet use in lowering the diagnosis of diabetes among AIs. This new information may mean that the internet is a good medium for health care information transfer among AIs. Public health personnel should also understand that AIs who do not have internet access are not privileged to use the expanded possibilities of online health-related information, and this may influence the higher diagnosis of diabetes among them. Providing incentives to non-profit community organizations to improve internet access, computer literacy, and technological resources among AIs who are older or from lower socioeconomic conditions must be considered at a policy level.

Moreover, if the association of having a personal doctor with higher odds of T2DM is due to reverse causation, there may be many AIs with no personal doctor living with undiagnosed T2DM. Focused attention to the AIs with no personal doctor is also valuable while addressing the issue of T2DM among AIs. Practitioners should be aware of this implication, reach out to the underprivileged communities, and identify AIs with undiagnosed T2DM for early diagnosis and management.

Research Implications

Nurse researchers focused on minority health can use these findings to conduct further research and add to the professional body of knowledge. This study findings generate various questions to be answered through further research. There was a significantly high proportion of higher BMI among AIs in this study. At the same time, the BMI was not significantly related to the diagnosis of T2DM when adjusted for age, sex, internet, and homeownership. This requires further exploration since there is contradicting information in the literature about the relationship of high BMI with a higher diagnosis of T2DM among AI (Commodore-Mensah et al., 2018). Fitzgerald et al. also reported in their study that BMIs of the vast majority of participants who had T2DM were in the obese category, however, the risk factors were not limited to obesity (Fitzgerald et al., 2020).

Furthermore, this study also indicated that having internet was associated with lower odds of T2DM, and having a personal doctor was associated with higher odds of T2DM. These findings require further exploration and research to clarify the paths of these relationships. This association of having a personal doctor with the diagnosis of T2DM could be attributed to reverse causation. This knowledge gap could be addressed by conducting longitudinal studies.

This study's findings should be considered in the context of the limitations of the study. Primary studies with survey tools tested for reliability and validity among AIs for assessing T2DM are recommended on this topic among AIs. Moreover, assuring heterogeneity of the AI sample is suggested for future research. In general, the theory did not completely explain the relationships that resulted from this study. Additional studies to develop new theories and establish new relationships that are relevant for the constantly evolving circumstances and living conditions are essential.

Conclusions

There is evidence in the literature about high SEP and unhealthy behaviors are related to the prevalence of T2DM among AIs in the US. However, these relationships were inconsistent and complex in many studies. This study findings indicate that age, internet use, and having a personal doctor are significantly associated with the DS prevalence in this study population. While age was positively associated with the diagnosis of DS, internet use was negatively associated with the diagnosis of DS. Having a personal doctor explained 14% and 8% of the variance in the relationship between internet use and the diagnosis of T2DM and DS respectively. However, the pathways of the relationship between the internet and personal doctor with the diagnosis of DS are yet to be understood. Further research is needed to better understand the nature of these relationships. The influence of other factors such as acculturation, emotional stress, and allostatic load on T2DM that have been explored in the other populations need to be studied among AIs in the US as well. The high proportion of increased BMI among AIs in the US established in this study also requires attention and call for action at the community level and policymaking. A longitudinal study design with culturally tailored tools, a more heterogenous sample, and a bigger sample size can provide valuable input on this topic impacting the care and treatment for AIs in the US.

References

Adler, N. E., Boyce, T., Chesney, M. A., Cohen, S., Folkman, S., Kahn, R. L., & Syme, S. L. (1994). Socioeconomic Status and Health: The Challenge of the Gradient. *Am Psychol*, *49*(1), 15-24. https://doi.org/10.1037/0003-066X.49.1.15

Agrawal, S., & Ebrahim, S. (2012). Prevalence and risk factors for self-reported diabetes among adult men and women in India: findings from a national cross-sectional survey. *Public Health Nutr*, *15*(6), 1065-1077. https://doi.org/10.1017/S1368980011002813

Agresti, A., & Finlay, B. (1986). *Statistical methods for the social sciences* (2nd ed. ed.). Dellen Pub. Co.

American Diabetes Association. (2017). *Statistics about Diabetes*. http://www.diabetes.org/diabetes-basics/statistics/?loc=db-slabnav

American Diabetes Association. (2018a). *The Cost of Diabetes*. http://www.diabetes.org/advocacy/news-events/cost-of-diabetes.html?loc=superfooter

American Diabetes Association. (2018b). *Statistics about diabetes*. American Diabetes Association. Retrieved March 3 from http://www.diabetes.org/diabetes-basics/statistics/

American Diabetes Association. (2021). *Understanding A1C*. ADA. https://www.diabetes.org/a1c/diagnosis

Amutha, A., Datta, M., Unnikrishnan, I. R., Anjana, R. M., Rema, M., Narayan, K. M., & Mohan, V. (2011). Clinical profile of diabetes in the young seen between 1992 and 2009 at a specialist diabetes centre in South India. *Prim Care Diabetes*, *5*(4), 223-229. https://doi.org/10.1016/j.pcd.2011.04.003

Anderson, L., & Fricker, R. D. J. *Raking: An Important and Often Overlooked Survey Analysis Tool*. Retrieved August 27,2019 from http://faculty.nps.edu/rdfricke/docs/RakingArticleV2.2.pdf

Anderson, N. J., & Marcum, J. L. (2019). Using Behavioral Risk Factor Surveillance System Data as an Occupational Health Profile: Washington State Janitors, 2011 to 2017. *Journal of occupational and environmental medicine*, *61*(9), 747-753. https://doi.org/10.1097/JOM.0000000000001652

Angel González Block, M. A., Sandiford, P., Arturo Ruiz, J., & Rovira, J. (2001). Beyond health gain:: the range of health system benefits expressed by social groups in Mexico and Central America. *Soc Sci Med*, *52*(10), 1537-1550. https://doi.org/10.1016/S0277-9536(00)00267-7 (Social Science & Medicine)

Anjana, R. M., Sudha, V., Nair, D. H., Lakshmipriya, N., Deepa, M., Pradeepa, R., Shanthirani, C. S., Subhashini, S., Malik, V., Unnikrishnan, R., Binu, V. S., Patel, S. A., Hu, F. B., & Mohan, V. (2015). Diabetes in Asian Indians—How much is preventable? Ten-year follow-up of the Chennai Urban Rural Epidemiology Study (CURES-142). https://doi.org/10.1016/j.diabres.2015.05.039

Announcement: Community Preventive Services Task Force Recommendation for Team-Based Care for Patients with Type 2 Diabetes. (2017). *MMWR Morb Mortal Wkly Rep*, *66*(23), 624. https://doi.org/10.15585/mmwr.mm6623a6

Aravindalochanan, V., Kumpatla, S., Rengarajan, M., Rajan, R., & Viswanathan, V. (2014). Risk of diabetes in subjects with sedentary profession and the synergistic effect of positive family history of diabetes. *Diabetes technology & therapeutics*, *16*(1), 26-32. https://doi.org/https://dx.doi.org/10.1089/dia.2013.0140

Bajaj, H. S., Pereira, M. A., Anjana, R. M., Deepa, R., Mohan, V., Mueller, N. T., Rao, G. H., & Gross, M. D. (2014). Comparison of relative waist circumference between Asian Indian and US adults. *J Obes*, *2014*, 461956. https://doi.org/10.1155/2014/461956

Baron, R. M., & Kenny, D. A. (1986). The Moderator-Mediator Variable Distinction in Social Psychological Research: Conceptual, Strategic, and Statistical Considerations. *Journal of personality and social psychology*, *51*(6), 1173-1182. https://doi.org/10.1037/0022-3514.51.6.1173

Batalova, J., & Zong, J. (2017). *Indian immigrants in the United States*. Migration Policy Institute. https://www.migrationpolicy.org/article/indian-immigrants-united-states

Bhardwaj, S., & Misra, A. (2015). Obesity, diabetes and the Asian phenotype. *World review of nutrition and dietetics*, *111*, 116-122. https://doi.org/https://dx.doi.org/10.1159/000362308

Boddula, R., Yadav, S., Bhatia, V., Genitta, G., Pandey, D., Kumar, A., Singh, H. K., Ramesh, V., Julka, S., Bansal, B., Srikant, K., & Bhatia, E. (2008). High prevalence of type 2 diabetes mellitus in affluent urban Indians. *Diabetes research and clinical practice*, *81*(2), e4-7. https://doi.org/https://dx.doi.org/10.1016/j.diabres.2008.04.003

Bopp, M., Wilcox, S., Laken, M., Butler, K., Carter, R. E., McClorin, L., & Yancey, A. (2006). Factors associated with physical activity among African-American men and women. *Am J Prev Med*, *30*(4), 340-346. https://doi.org/10.1016/j.amepre.2005.11.007

Bujang, M. A., Sa'at, N., Sidik, T. M. I. T. A. B., & Joo, L. C. (2018). Sample Size Guidelines for Logistic Regression from Observational Studies with Large Population: Emphasis on the Accuracy Between Statistics and Parameters Based on Real Life Clinical Data. *The Malaysian journal of medical sciences*, *25*(4), 122-130. https://doi.org/10.21315/mjms2018.25.4.12

CDC. *Behavioral Risk Factor Surveillance System*. USA.gov. Retrieved 8.26.2019 from https://www.cdc.gov/brfss/about/index.htm

CDC. (2016). *Behavioral Risk Factor Surveillance System OVERVIEW: BRFSS 2016*. https://www.cdc.gov/brfss/annual_data/2016/pdf/overview_2016.pdf

CDC. (2018). *The Behavioral Risk Factor Surveillance System 2017 Summary Data Quality Report*. https://www.cdc.gov/brfss/annual_data/2017/pdf/2017-sdqr-508.pdf

CDC. (2019). *2018 BRFSS survey data and documentation*. https://www.cdc.gov/brfss/annual_data/annual_2018.html

CDC. (2020). *About Adult BMI*. Centers for Disease Control and Prevention. https://www.cdc.gov/healthyweight/assessing/bmi/adult_bmi/index.html#Interpreted

Clark, S. R., & Wilson, M. L. (2016). Original Research: Early Diabetes

Screening in the Urgent Care, Part 2. *The Journal of Urgent Care Medicine*, 28-33.

Commodore-Mensah, Y., Selvin, E., Aboagye, J., Turkson-Ocran, R. A., Li, X. M., Himmelfarb, C. D., Ahima, R. S., & Cooper, L. A. (2018). Hypertension, overweight/obesity, and diabetes among immigrants in the United States: an analysis of the 2010-2016 National Health Interview Survey. *BMC Public Health*, *18*, Article 773. https://doi.org/10.1186/s12889-018-5683-3

Cotter, A. P., Durant, N., Agne, A. A., & Cherrington, A. L. (2014). Internet interventions to support lifestyle modification for diabetes management: a systematic review of the evidence. *J Diabetes Complications*, *28*(2), 243-251. https://doi.org/10.1016/j.jdiacomp.2013.07.003

Cowie, C. C. (2019). Diabetes Diagnosis and Control: Missed Opportunities to Improve Health : The 2018 Kelly West Award Lecture. *Diabetes Care*, *42*(6), 994-1004. https://doi.org/10.2337/dci18-0047

Daniel, M., Wilbur, J., Marquez, D., & Farran, C. (2013). Lifestyle Physical Activity Behavior Among South Asian Indian Immigrants. *Journal of Immigrant and Minority Health*, *15*(6), 1082-1089. https://doi.org/10.1007/s10903-013-9842-4

Denis Anthony, Rob Baggott, Judith Tanner, Kathryn Jones, Hala Evans, Gill Perkins, & Hilary Palmer. (2012). Health, lifestyle, belief and knowledge differences between two ethnic groups with specific groups with specific reference to tobacco,diet and physical activity. *Journal of Advanced Nursing*. https://doi.org/10.1111/j.1365-2648.2012

Department of Health and Human Services, O. o. M. H. (2020). *Minority population profiles*. HHS.gov. https://minorityhealth.hhs.gov/omh/browse.aspx?lvl=2&lvlID=26

Dhar, S., Gor, B., Banerjee, D., Krishnan, S., Dorai, V. K., Jones, L., Kabad, K., Naik, L. R., Legha, S. S., & Pande, M. (2019). Differences in nativity, age and gender may impact health behavior and perspectives among Asian Indians. *Ethn Health*, *24*(5), 484-494. https://doi.org/10.1080/13557858.2017.1346783

Diderichsen F, & Hallqvist J. (1998). Social inequalities in health: some methodological considerations for the study of social position and social context. *Arve-Parés B, ed. Inequality in health—a Swedish perspective*. (Stockholm: Swedish Council for Social Research)

Fagherazzi, G., & Ravaud, P. (2019). Digital diabetes: Perspectives for diabetes prevention, management and research. *Diabetes & Metabolism*, *45*(4), 322-329. https://doi.org/10.1016/j.diabet.2018.08.012

Fang, J., Keenan, N. L., Ayala, C., Dai, S., & Valderrama, A. L. (2010). Fruits and Vegetables Intake and Physical Activity Among Hypertensive Adults in the United States: Behavioral Risk Factor Surveillance System, 2003 and 2007. *American journal of hypertension*, *23*(7), 762-766. https://doi.org/10.1038/ajh.2010.46

Fitzgerald, N., Mathur, S., & Dutta, S. (2020). P159 Participant Characteristics in a Community-Based Diabetes Education Program for South Asians. *Journal of Nutrition Education and Behavior*, *52*(7), S91-S92. https://doi.org/10.1016/j.jneb.2020.04.207

Fleming, E., Carter, B., & Pettigrew, J. (2008). The influence of culture on diabetes self-management: perspectives of Gujarati Muslim men who reside in northwest England. *J Clin Nurs*, *17*(5a), 51-59. https://doi.org/10.1111/j.1365-2702.2007.02178.x

Gadgil, M. D., Anderson, C. A., Kandula, N. R., & Kanaya, A. M. (2014). Dietary patterns in Asian Indians in the United States: an analysis of the metabolic syndrome and atherosclerosis in South Asians Living in America study. *J Acad Nutr Diet*, *114*(2), 238-243. https://doi.org/10.1016/j.jand.2013.09.021

Gadgil, M. D., Anderson, C. A. M., Kandula, N. R., & Kanaya, A. M. (2015). Dietary patterns are associated with metabolic risk factors in South Asians living in the United States. *The Journal of nutrition*, *145*(6), 1211-1217. https://doi.org/10.3945/jn.114.207753

Ghai, N. R., Jacobsen, S. J., Van Den Eeden, S. K., Ahmed, A. T., Haque, R., & Quinn, V. P. (2012). A Comparison of Lifestyle and Behavioral Cardiovasular Disease Risk Factors Between Asian Indian and White Non Hispanic Man. *Ethnicity and Disease*, *22*(2), 168-174. https://www.ethndis.org/edonline/index.php/ethndis/article/view/501/553

Ghorpade, A., Majgi, S., Sarkar, S., Sekhar Kar, S., Roy, G., Ananthanarayanan, P., & Das, A. (2013). Diabetes in rural Pondicherry, India: a population-based study of the incidence and risk factors. *WHO South East Asia J Public Health*, *2*(3-4), 149-155. https://doi.org/10.4103/2224-3151.115828

Gujral, U. P., Mohan, V., Pradeepa, R., Deepa, M., Anjana, R. M., Mehta, N. K., Gregg, E. W., & Narayan, K. M. (2016). Ethnic variations in diabetes and prediabetes prevalence and the roles of insulin resistance and β-cell function: The CARRS and NHANES studies. https://doi.org/10.1016/j.jcte.2016.02.004

Gujral, U. P., Narayan, K. M., Pradeepa, R. G., Deepa, M., Ali, M. K., Anjana, R. M., Kandula, N. R., Mohan, V., & Kanaya, A. M. (2015). Comparing type 2 diabetes, prediabetes, and their associated risk factors in Asian Indians in India and in the U.S.: The CARRS and MASALA Studies. *Diabetes Care*, *38*(7), 1312-1318. https://doi.org/10.2337/dc15-0032

Gupta, R., Deedwania, P. C., Sharma, K., Gupta, A., Guptha, S., Achari, V., Asirvatham, A. J., Bhansali, A., Gupta, B., Gupta, S., Jali, M. V., Mahanta, T. G., Maheshwari, A., Saboo, B., Singh, J., & Gupta, R. (2012). Association of Educational, Occupational and Socioeconomic Status with Cardiovascular Risk Factors in Asian Indians: A Cross-Sectional Study [Article]. *PLOS ONE*, *7*(8), 10, Article e44098. https://doi.org/10.1371/journal.pone.0044098

He, L., Tuomilehto, J., Qiao, Q., Söderberg, S., Daimon, M., Chambers, J., & Pitkäniemi, J. (2015). Impact of classical risk factors of type 2 diabetes among Asian Indian, Chinese and Japanese populations for the DECODA study group. *Diabetes & Metabolism*, *41*, 401-409. https://doi.org/10.1016/j.diabet.2015.07.003

Jahangiry, L., Shojaeizadeh, D., Najafi, M., Mohammad, K., Abbasalizad Farhangi, M., & Montazeri, A. (2014). 'Red Ruby': an interactive web-based intervention for lifestyle modification on metabolic syndrome: a study protocol for a randomized controlled trial. *BMC Public Health*, *14*(1), 748-748. https://doi.org/10.1186/1471-2458-14-748

Jara, A. J., Zamora, M. A., & Skarmeta, A. F. G. (2011). An internet of things–based personal device for diabetes therapy management in ambient assisted living (AAL). *Personal and ubiquitous computing*, *15*(4), 431-440. https://doi.org/10.1007/s00779-010-0353-1

Joo, J. Y. (2014). Effectiveness of culturally tailored diabetes interventions for Asian immigrants to the United States: a systematic review. *Diabetes Educ*, *40*(5), 605-615. https://doi.org/10.1177/0145721714534994

Joseph, N. M., Misra, R., Wang, J., Cron, S., & Ramaswamy, P. (2018). Mediating Role of Acculturation and Lifestyle Behaviors on Cardiometabolic Risks among Asian Indians in the United States. *Diabetes*, *67*(Supplement 1), 247-OR-OR. https://doi.org/10.2337/db18-247-OR

Joshi, S. R. (2012). Type 2 diabetes in Asian Indians. *Clin Lab Med*, *32*(2), 207-216. https://doi.org/10.1016/j.cll.2012.04.012

Kanaya, A. M., Herrington, D., Vittinghoff, E., Ewing, S. K., Liu, K., Blaha, M. J., Dave, S. S., Qureshi, F., & Kandula, N. R. (2014). Understanding the high prevalence of diabetes in U.S. South Asians compared with four racial/ethnic groups: the MASALA and MESA studies. *Diabetes Care*, *37*(6), 1621. https://doi.org/10.2337/dc13-2656

Kanaya, A. M., wasswl, C. L., Mathur, D., Stewart, A., D., H., & J, B. M. (2010). Prevalence and correlates of diabetes in South Asian Indians in the United States: findings from the Metabolic Syndrome and Atherosclerosis in South Asians Living in America study and the Multi-Ethnic Study of Atherosclerosis. *Metabolic syndrome and related disorders*, *8*(2). https://doi.org/https://doi-org.proxy.libraries.rutgers.edu/10.1089/met.2009.0062

Khardori, R. (2019). *Type 2 Diabetes Mellitus*. Medscape. Retrieved 4/5/2019 from https://emedicine.medscape.com/article/117853-overview

Kooner, J. S., Saleheen, D., Sim, X., Sehmi, J., Zhang, W., Frossard, P., Been, L. F., Chia, K. S., Dimas, A. S., Hassanali, N., Jafar, T., Jowett, J. B., Li, X., Radha, V., Rees, S. D., Takeuchi, F., Young, R., Aung, T., Basit, A., Chidambaram, M., Das, D., Grundberg, E., Hedman, A. K., Hydrie, Z. I., Islam, M., Khor, C. C., Kowlessur, S., Kristensen, M. M., Liju, S., Lim, W. Y., Matthews, D. R., Liu, J., Morris, A. P., Nica, A. C., Pinidiyapathirage, J. M., Prokopenko, I., Rasheed, A., Samuel, M., Shah, N., Shera, A. S., Small, K. S., Suo, C., Wickremasinghe, A. R., Wong, T. Y., Yang, M., Zhang, F., Diagram, MuTher, Abecasis, G. R., Barnett, A. H., Caulfield, M., Deloukas, P., Frayling, T. M., Froguel, P., Kato, N., Katulanda, P., Kelly, M. A., Liang, J., Mohan, V., Sanghera, D. K., Scott, J., Seielstad, M., Zimmet, P. Z., Elliott, P., Teo, Y. Y., McCarthy, M. I., Danesh, J., Tai, E. S., & Chambers, J. C. (2011). Genome-wide association study in individuals of South Asian ancestry identifies six new type 2 diabetes susceptibility loci. *Nat Genet*, *43*(10), 984-989. https://doi.org/10.1038/ng.921

Kruse, R. L., Koopman, R. J., Wakefield, B. J., Wakefield, D. S., Keplinger, L. E., Canfield, S. M., & Mehr, D. R. (2012). Internet use by primary care patients: where is the digital divide? *Family medicine*, *44*(5), 342-347.

Lee, J. W. R., Brancati, F. L., & Yeh, H.-c. (2011). Trends in the prevalence of type 2 diabetes in Asians versus Whites: Results from the United States National Health Interview Survey, 1997-2008.(ORIGINAL ARTICLE: Epidemiology/Health Services Research). *Diabetes Care*, *34*(2), 353. https://doi.org/10.2337/dc10-0746

MacKinnon, D. (2008). *Introduction to Statistical Mediation Analysis*. Taylor & Francis Group.

Martin-Timon, I., Sevillano-Collantes, C., Segura-Galindo, A., & Del Canizo-Gomez, F. J. (2014). Type 2 diabetes and cardiovascular disease: Have all risk factors the same strength? *World J Diabetes*, *5*(4), 444-470. https://doi.org/10.4239/wjd.v5.i4.444

Mayben, J. K., & Giordano, T. P. (2007). Internet use among low-income persons recently diagnosed with HIV infection. *AIDS care*, *19*(9), 1182-1187. https://doi.org/10.1080/09540120701402806

McCoy, M. R., Couch, D., Duncan, N. D., & Lynch, G. S. (2005). Evaluating an Internet weight loss program for diabetes prevention. *Health promotion international*, *20*(3), 221-228. https://doi.org/10.1093/heapro/dai006

Mehrotra, N., Gaur, S., & Petrova, A. (2012). Health Care Practices of the Foreign Born Asian Indians in the United States. A Community Based Survey. *Journal of Community Health*, *37*(2), 328-334. https://doi.org/10.1007/s10900-011-9449-4

Misra, A., Ramchandran, A., Jayawardena, R., Shrivastava, U., & Snehalatha, C. (2014). Diabetes in South Asians. *Diabet Med*, *31*(10), 1153-1162. https://doi.org/10.1111/dme.12540

Misra, A., Soares, M. J., Mohan, V., Anoop, S., Abhishek, V., Vaidya, R., & Pradeepa, R. (2018). Body fat, metabolic syndrome and hyperglycemia in South Asians. *J Diabetes Complications*, *32*(11), 1068-1075. https://doi.org/10.1016/j.jdiacomp.2018.08.001

Misra, R., Balagopal, P., Raj, S., & Patel, T. G. (2018). Vegetarian Diet and Cardiometabolic Risk among Asian Indians in the United States. *J Diabetes Res*, *2018*, 1675369. https://doi.org/10.1155/2018/1675369

Moore, L. V., Dodd, K. W., Thompson, F. E., Grimm, K. A., Kim, S. A., & Scanlon, K. S. (2015). Using Behavioral Risk Factor Surveillance System Data to Estimate the Percentage of the Population Meeting US Department of Agriculture Food Patterns Fruit and Vegetable Intake Recommendations. *American journal of epidemiology*, *181*(12), 979-988. https://doi.org/10.1093/aje/kwu461

Mukherjea, A., Underwood, K. C., Stewart, A. L., Ivey, S. L., & Kanaya, A. M. (2013). Asian Indian views on diet and health in the United States: importance of understanding cultural and social factors to address disparities. *Fam Community Health*, *36*(4), 311-323. https://doi.org/10.1097/FCH.0b013e31829d2549

Mukherjee, S., Thakur, G., Kumar, B. D., Mitra, A., & Chakraborty, C. (2009). Long-term effects of a carbohydrate-rich diet on fasting blood sugar, lipid profile, and serum insulin values in rural Bengalis. *J Diabetes*, *1*(4), 288-295. https://doi.org/https://dx.doi.org/10.1111/j.1753-0407.2009.00050.x

Nagarathna, R., Kaur, N., Anand, A., Sharma, K., Dada, R., Sridhar, P., Sharma, P., Kumar Singh, A., Patil, S., & Nagendra, H. R. (2020). Distribution of glycated haemoglobin and its determinants in Indian young adults. *Diabetes Res Clin Pract*, *159*, 107982. https://doi.org/10.1016/j.diabres.2019.107982

Newschaffer, C., & Counte, M. (1998). *Validation of Behavioral Risk Factor Surveillance System (BRFSS) HRQOL Measures in a Statewide Sample*.

Nguyen, A. B., Moser, R., & Chou, W. Y. (2014). Race and health profiles in the United States: an examination of the social gradient through the 2009 CHIS adult survey. *Public Health*, *128*(12), 1076-1086. https://doi.org/10.1016/j.puhe.2014.10.003

O'Keefe, E. L., DiNicolantonio, J. J., Patil, H., Helzberg, J. H., & Lavie, C. J. (2016). Lifestyle Choices Fuel Epidemics of Diabetes and Cardiovascular Disease Among Asian Indians. *Progress in Cardiovascular Diseases*, *58*(5), 505-513. https://doi.org/10.1016/j.pcad.2015.08.010

O’Keefe, E. L., DiNicolantonio, J. J., Patil, H., Helzberg, J. H., Lavie, C. J., O'Keefe, E. L., DiNicolantonio, J. J., Patil, H., Helzberg, J. H., & Lavie, C. J. (2016). Lifestyle Choices Fuel Epidemics of Diabetes and

Cardiovascular Disease Among Asian Indians. *Science direct*, *58*(5). https://doi.org/10.1016/j.pcad.2015.08.010

Odds ratio-sample size. (2019). Select Statistical Services. Retrieved 12.20.2019 from https://select-statistics.co.uk/calculators/sample-size-calculator-odds-ratio/

Pew Charitable Trusts. (2014). *Changing patterns in U.S. immigration and population: Immigrants slow population decline in many counties*. http://www.pewtrusts.org/en/research-and-analysis/issue-briefs/2014/12/changing-patterns-in-us-immigration-and-population

Pierannunzi, C., Hu, S. S., & Balluz, L. (2013). A systematic review of publications assessing reliability and validity of the Behavioral Risk Factor Surveillance System (BRFSS), 2004-2011 [Article]. *BMC Medical Research Methodology*, *13*(1), 1-14. https://doi.org/10.1186/1471-2288-13-49

Radhika, G., Sathya, R. M., Ganesan, A., Saroja, R., Vijayalakshmi, P., Sudha, V., & Mohan, V. (2011). Dietary profile of urban adult population in South India in the context of chronic disease epidemiology (CURES-68). *Public Health Nutrition*, *14*(4), 591-598. https://doi.org/https://dx.doi.org/10.1017/S136898001000203X

Ram, J., Selvam, S., Snehalatha, C., Nanditha, A., Simon, M., Shetty, A. S., Godsland, I. F., Johnston, D. G., & Ramachandran, A. (2014). Improvement in diet habits, independent of physical activity helps to reduce incident diabetes among prediabetic Asian Indian men. *Diabetes research and clinical practice*, *106*(3), 491-495. https://doi.org/https://dx.doi.org/10.1016/j.diabres.2014.09.043

Ram, R., Goswami, D. N., Bhattacharya, S. K., Bhattacharya, K., Saha, B. K., Saha, J., & Baur, B. (2006). An epidemiological study on risk factors of diabetes mellitus among patients attending a medical college hospital in Kolkata, West Bengal. *Journal of the Indian Medical Association*, *104*(8), 428-430. http://ovidsp.ovid.com/ovidweb.cgi?T=JS&PAGE=reference&D=med5&NEWS=N&AN=17240798

Ramachandran, A., Snehalatha, C., & Vijay, V. (2002). Temporal changes in prevalence of type 2 diabetes and impaired glucose tolerance in urban southern India. *Diabetes research and clinical practice*, *58*(1), 55-60. http://ovidsp.ovid.com/ovidweb.cgi?T=JS&PAGE=reference&D=med4&NEWS=N&AN=12161057

Roncancio, A. M., Berenson, A. B., & Rahman, M. (2012). Health locus of control, acculturation, and health-related Internet use among Latinas. *J Health Commun*, *17*(6), 631-640. https://doi.org/10.1080/10810730.2011.635767

Rowley, W. R., Bezold, C., Arikan, Y., Byrne, E., & Krohe, S. (2017). Diabetes 2030: Insights from Yesterday, Today, and Future Trends. *Popul Health Manag*, *20*(1), 6-12. https://doi.org/10.1089/pop.2015.0181

Rubina Tabassum, Ganesh Chauhan, Om Prakash Dwivedi, Anubha Mahajan, Alok Jaiswal, Ismeet Kaur, Khushdeep Bandesh, Tejbir Singh, Benan John Mathai, Yogesh Pandey, Manickam Chidambaram, Amitabh Sharma, Sreenivas Chavali, Shantanu Sengupta, Lakshmi Ramakrishnan, Pradeep Venkatesh, Sanjay K. Aggarwal, Saurabh Ghosh, Dorairaj Prabhakaran, Reddy K. Srinath, Madhukar

Saxena, Monisha Banerjee, Sandeep Mathur, Anil Bhansali, Viral N. Shah, Sri Venkata Madhu, Raman K. Marwaha, Analabha Basu, Vinod Scaria, Mark I. McCarthy, Radha Venkatesan, Viswanathan Mohan, Nikhil Tandon, & Dwaipayan Bharadwaj. (2013). Genome-Wide Association Study for Type 2 Diabetes in

Indians Identifies a New Susceptibility Locus at 2q21. *Diabetes.diabetes journals.org*. https://doi.org/10.2337/db12-0406

Salkind, N. J. (2014). *Statistics for People Who Hate Statistics*. Sage publishers.

Shah, V. N., & Mohan, V. (2015). Diabetes in India: what is different? *Curr Opin Endocrinol Diabetes Obes*, *22*(4), 283-289. https://doi.org/10.1097/MED.0000000000000166

Shivane, V. K., Lila, A. R., & Bandgar, T. R. (2020). Type 2 diabetic Asian Indians and COVID-19: Lessons learnt so far from the ongoing pandemic. *J Postgrad Med*, *66*(4), 179-181. https://doi.org/10.4103/jpgm.JPGM_602_20

Shrivastava, S. R., & Ghorpade, A. G. (2014). High Prevalence of Type 2 Diabetes Melitus and Its Risk Factors Among the Rural Population of Pondicherry, South India. *Journal of research in health sciences*, *14*(4), 258-263.

Solar, O., & Irwin, A. (2010). *A Conceptual Framework for Action on the Social Determinants of Health* W. D. P. Services. http://apps.who.int/iris/bitstream/10665/44489/1/9789241500852_eng.pdf?ua=1

Southam, L., Soranzo, N., Montgomery, S. B., Frayling, T. M., McCarthy, M. I., Barroso, I., & Zeggini, E. (2009). Is the thrifty genotype hypothesis supported by evidence based on confirmed type 2 diabetes- and obesity-susceptibility variants? *Diabetologia*, *52*(9), 1846-1851. https://doi.org/10.1007/s00125-009-1419-3

Tiagi, R. (2013). Economic Assimilation of Asian Indians in the United States: Evidence from the 1990s. *Journal of international migration and integration*, *14*(3), 511-534. https://doi.org/10.1007/s12134-012-0252-6

Valeri, L., & VanderWeele, T. J. (2013). Mediation Analysis Allowing for Exposure-Mediator Interactions and Causal Interpretation: Theoretical Assumptions and Implementation With SAS and SPSS Macros. *Psychological Methods*, *18*(2), 137-150. https://doi.org/10.1037/a0031034

VanderWeele, T. J. (2014). A unification of mediation and interaction: a four-way decomposition. *Epidemiology (Cambridge, Mass.)*, *25*(5), 749-761. https://doi.org/10.1097/EDE.0000000000000121

Venkat Narayan, K. M., Kondal, D., Kobes, S., Deepa, M., Daya, N. R., Patel, S. A., Anjana, R. M., Staimez, L. R., Ali, M. K., Gujral, U., Prabhakaran, D., Shivashankar, R., Kadir, M., Selvin, E., Mohan, V., Hanson, R. L., & Tandon, N. (2019). 1597-P: Incidence of Diabetes in Young Adult South Asians Compared with Pima Indians. *Diabetes (New York, N.Y.)*, *68*(Supplement 1), 1597. https://doi.org/10.2337/db19-1597-P

Venkataraman, R., Nanda, N. C., Baweja, G., Parikh, N., & Bhatia, V. (2004). Prevalence of diabetes mellitus and related conditions in Asian Indians living in the United States. *Am J Cardiol*, *94*(7), 977-980. https://doi.org/10.1016/j.amjcard.2004.06.048

Venkatesh, S., Conner, T., Song, W. O., Olson, B. H., & Weatherspoon, L. J. (2017). The Relationship Between Dietary Acculturation and Type 2 Diabetes Risk Among

Asian Indians in the U.S. *Journal of Immigrant and Minority Health*, *19*(2), 294-301. https://doi.org/https://dx.doi.org/10.1007/s10903-016-0482-3

Vijayakumar, G., Manghat, S., Vijayakumar, R., Simon, L., Scaria, L. M., Vijayakumar, A., Sreehari, G. K., Kutty, V. R., Rachana, A., & Jaleel, A. (2019). Incidence of type 2 diabetes mellitus and prediabetes in Kerala, India: results from a 10-year prospective cohort. *BMC Public Health*, *19*(1), 140. https://doi.org/10.1186/s12889-019-6445-6

World Health Organization. (2008). *Social Determinants of Health*. World Health Organization. Retrieved January 16 from https://www.who.int/social_determinants/sdh_definition/en/

Ye, J., Rust, G., Baltrus, P., & Daniels, E. (2009). Cardiovascular risk factors among Asian Americans: results from a National Health Survey. *Ann Epidemiol*, *19*(10), 718-723. https://doi.org/10.1016/j.annepidem.2009.03.022

Yoon, H., Jang, Y., Vaughan, P. W., & Garcia, M. (2020). Older Adults' Internet Use for Health Information: Digital Divide by Race/Ethnicity and Socioeconomic Status. *Journal of applied gerontology*, *39*(1), 105-110. https://doi.org/10.1177/0733464818770772

Zhang, Y. L., & Tsai, J. L. (2014). The Assessment of Acculturation, enculturation, and culture in Asian- American Sample. *Guide to Psychological Assessment with Asians*, 75-101. https://doi.org/https://doi.org/10.1007/978-1-4939-0796-0_6

Appendix 1

Evidence Table

Author/Year	Sample	Study Purpose	Study type	Analysis	Concepts/ Measures	Relevant findings/ Limitations
Structural SDH and T2DM Prevalence						
Gujral U.P/ 2015	AIs Age-40-84 years <u>Group 1</u> Number-757 Place-San Francisco or Chicago Years-2010-2013 MASALA- Random sampling from desired locations <u>Group 2</u> Number-2305 Place-Chennai, India Years-2010-2011 CARRS - Multistage cluster sampling and within household participant selection	To assess the prevalence and associated risk factors of diabetes and prediabetes in two Asian Indian population living in two different environments	Cross sectional study	Odds ratio and confidence intervals, chi square, ANOVA, regression analysis	Researcher administered questionnaire, Self-reported use of glucose lowering medications, fasting glucose levels, and 2 hours post prandial glucose levels	<u>Relevant Findings</u> 1) Age adjusted diabetes prevalence is higher in India (38% [95% CI 36-40]) than in the US (24% [95% CI 21-27]). 2) Age adjusted prediabetes prevalence is lower in India (24% [95% CI 22-26]) than in the US (33% [95% CI 30-36]). 3) After adjusting for age, sex, waste circumference, and systolic pressure, living in the US was associated with an increased odd for prediabetes (odds ratio 1.2 [95% CI 0.9-1.5]) and a decreased odd for diabetes (odds ratio 0.5 [95% CI 0.4-0.6]). 4) Mean BMI was higher in the US 5) Inclusion of height as a proxy for socioeconomic status and education together in multivariable models significantly attenuated the effect of place of residence on the odds of having diabetes. <u>Limitations</u>

						1) AIs living in other parts of India or the U.S are not represented.
Nguyen A.B/ 2014	47,200 adults 2009 California Health Interview Survey (CHIS) A multistage sampling design and a random digit dial telephone survey Weighted samples selected by counties	To examine the role of the social gradient on multiple health outcomes and behaviors	Cross sectional study Secondary data analysis	Weighted unadjusted linear and logistic regression models	Concepts SES (educational attainment or family income) Health conditions (limited physical activity due to chronic condition, high blood pressure, obesity, BMI, diabetes, and perceived health conditions) Measure Self-reported survey	Relevant Findings Racial/ethnic disparities in health outcomes are most pronounced in the lowest SEP Asians in the upper two levels of SEP in both education and family income demonstrate the healthiest measures of health status (physical activity limited due to chronic condition, high blood pressure, obesity, diabetes, and BMI) Asians show curvilinear trends of the social gradient (i.e. An initial increase from low SES to mid-level SES was associated with worse health outcomes and behaviors and continued increase from mid-SES to high SES saw returns to healthy outcomes and behaviors). Limitations Asian Indians are represented as part of Asians. Generational status or length of residency in the US may moderate the strength of the social gradient in health. Reverse causation can occur with income.
Gupta/ 2012	Adults 18-75 years of age from 11 cities of India. Simple cluster sampling Sample size 6198	To determine the prevalence of cardiovascular risk factors in urban Indian population	Cross sectional study	Non-parametric Kendall's B test, Chi square, Odds ratio	Concepts Socioeconomic status Education, occupation, and social status. T2DM prevalence	Relevant Findings Diabetes prevalence was similar in across all socioeconomic groups (*p*<.05). Limitations Study was conducted in India**.** Only people from urban area were included in the study

	Response rate 69%			and 95% CI, Multivariate logistic regression	<u>Measures</u> Self-reported questionnaire, Anthropometric assessments by measurement. Blood glucose assessments.	
Misra R/ 2018	1038 randomly selected AIs, aged 18 years and older, from seven US cities	To explore the relationship between the consumption of a traditional Asian Indian vegetarian diet and the prevalence of T2DM, obesity, and metabolic syndrome among AIs residing in the United States, after controlling for acculturation, dietary	Secondary data analysis of DIA study in 2010	Logistic regression analysis	<u>Concepts</u> 1. Demographic characteristics. (age, number of years in the US, gender, education, marital status, income, access to health care, self-rated health, English proficiency, and family history of diabetes) 2. Self-reported dietary behavior from nutrition subscale 3. Fasting capillary	Participants with higher incomes had a higher risk for diabetes (OR = 1.87; 95% CI = 1.06, 3.55) <u>Limitations</u> May include social desirability bias since the survey was self-reported.

		and lifestyle habits, family history of diabetes, knowledge of diabetes and CVD risk factors, and demographic characteristics			glucose (mg/dL) 4. Lifestyle factors (dietary habits, body mass index, spirituality, physical activity, and tobacco use) <u>Measures</u> Self-reported questionnaire, Fasting glucose test in the original study	
Kanaya/ 2010	150 adult AIs In the US Random sampling. Sampling frame South Asian surnames	To determine the prevalence and correlates of T2DM and prediabetes in AIs compared to other US ethnic groups.	Cross sectional study	Chi square test, ANOVA Proportional odds regression models, Unadjusted, age adjusted, multivariate adjusted logistic regression models	Physical activity, smoking, alcohol medical history assessed through Self-reported questionnaires, Clinical measurements to assess prevalence and correlates of T2DM	<u>Relevant findings</u> T2DM prevalence unadjusted 23% adjusted 29%. After adjusting for all the confounders other races have lower odds of T2DM than AIs OR=0.17 for Whites, 0.37 for Latinos, 0.50 for African Americans, 055 for Chinese Americans. Moderate/strong traditional Indian beliefs was independently associated with increased odds of prediabetes or diabetes. Tradition of serving sweets at religious ceremonies, fasting on specific occasions, and having an arranged marriage had the strongest associations. There was no association between socioeconomic status, education, and family income, and the prevalence of diabetes.

						Limitations Small sample size Study is cross sectional in nature
Agrawal S./2012	99574 adult women,56744 adult men from all states of India. The survey had 98% response rate	To describe the geographic variation in T2DM prevalence of and to examine the effect of modifiable risk factors on T2DM prevalence.	Cross-sectional study. Secondary data analysis of national health survey of 2005-2006	Descriptive statistics, Logistic regression analysis, odds ratio	Interviewer administered Questionnaire of demographic, socioeconomicand health content.	Relevant findings Education had no effect on diabetes prevalence. Wealthier people had more prevalence of T2DM mediated through obesity. Limitations This data is older than15 years. Possibility of social desirability bias due to self-reporting.
Boddula R./2008	1112 adults of upper SEP in India.	To describe the prevalence of T2DM among affluent urban Indians	Quantitative cross-sectional study	t-test chi square, ANOVA, logistic regression	Interviewer administered, previously validated questionnaire, Anthropometric measurements, OGTT, fasting and postprandial glucose tests, Physical assessment for height, weight, blood pressure.	Relevant findings Income, occupation, and physical activity were not significantly associated with prevalence of T2DM. T2DM prevalence 21.1% 43% overweight, 32%obese,87% central obesity. Limitations This data is older >15 years. Only people of upper SEP were included in the study.

Shrivastava S./2014	339 adults in rural South India	To assess the prevalence and the determinants of T2DM in the rural population of Pondicherry.	Cross sectional descriptive study	t-test, chi-square, logistic regression model	Pretested behavior questionnaire for socio demographic assessment Physical assessment for height, weight, blood pressure Lab tests Lipid profile, post prandial blood sugar, Fasting blood glucose, HBA1C.	<u>Relevant Findings</u> Higher education, being unemployed and poor increased the diagnosis of diabetes. After adjusting for risk factors, higher age, education, and income were significant risk factors. <u>Limitations</u> Dietary assessment was done by single contact data.
Structural and Intermediary SDH						
Mehrotra N./2012	1016 foreign born Asian Indian adults in the US Convenient sampling 73.5% response rate	To evaluate health care practices, self-health perception, and satisfaction with medical care	Cross sectional study	Linear regression analysis	Health related practices, self-health perception, and satisfaction with medical care/ smoking, use of seat belt, alcohol and tobacco use, and frequency of exercises activity for 30 min or more, known medical conditions, compliance with annual routine medical	<u>Relevant findings</u> Regular medical examinations compliance was directly associated with income and not with other characteristics including gender, age, insurance coverage, education, employment, chronic conditions, and duration of the stay in the US. 2) Exercise comparable to CDC recommendations for 71.3%. 3) Abstinence from tobacco and alcohol 96.4 and 67.3% respectively <u>Limitations</u> 1) Convenient sampling, 2) Mostly socioeconomically advantaged group

					examination testing of blood pressure and general metabolic profile blood glucose and cholesterol, mammogram, self-breast exams, pap smear, prostate assessment. <u>Measure</u> Self-administered survey questionnaire.	3) Too small sample size to identify variations among people from different regions of India 4)PA was graded as per CDC recommendations but Asian Indian specific guidelines are much higher and not met. 5)Self-reported survey method, can lead to reporting bias.
Gadgil/2014	150 AIs 45-84 years of age in San Francisco Random sampling. Sampling frame South Asian surnames	To examine the associations of dietary patterns with components of the metabolic syndrome, lipid levels, hormones, cytokines produced by adipose tissue, and subcutaneous and visceral fat	Cross-sectional study	Chi square and linear regression analyses Principal component analysis by varimax rotation.	South Asian food frequency questionnaire Weight - digital scale Height- stadiometer WC by measuring tape In person interview X-ray absorptiometry	<u>Relevant Findings</u> There were no differences in age, BMI, income, level of education, exercise, cigarette smoking, diabetes status, or traditional Indian beliefs by dietary pattern. <u>Limitations</u> Pilot study Small sample size Study was cross sectional in nature.

		content in participants in the Metabolic syndrome and Atherosclerosis in South Asians Living in America (MASALA) pilot study				
Nguyen A.B/ 2014	47,200 adults 2009 California Health Interview Survey (CHIS) A multistage sampling design and a random digit dial telephone survey Weighted samples selected by counties	To examine the role of the social gradient on multiple health outcomes and behaviors	Cross sectional study Secondary data analysis	Weighted unadjusted linear and logistic regression models	<u>Concepts</u> SES(educational attainment or family income) Health conditions (limited physical activity due to chronic condition, high blood pressure, obesity, BMI, diabetes, and perceived health conditions) <u>Measure</u> Self-reported survey	<u>Relevant Findings</u> Asians show curvilinear trends of the social gradient (i.e. An initial increase from low SEP to mid-level SEP was associated with worse health outcomes and unhealthy behaviors and continued increase from mid-SEP to high SEP saw returns to healthy outcomes and health behaviors). <u>Limitations</u> AIs are represented as part of Asians. Generational status or length of residency in the US may moderate the strength of the social gradient in health. Reverse causation can occur with income.
Gupta/2012	Adults 18-75 years of age from 11 cities of India.	To determine the prevalence of	Cross sectional	Non-parametric Kendall	<u>Concepts</u> Socioeconomic status	<u>Relevant Findings</u> Smoking/tobacco use (OR 3.27,95% CI 2.66-4.01), low physical activity (1.15,0.97-1.37), low fruit and vegetable

	Simple cluster sampling Sample size 6198 Response rate 69%	cardiovascular risk factors in urban Indian population	study	's B test, Chi square, Odds ratio and 95% CI, Multivariate logistic regression	Education, occupation, and social status. T2DM prevalence Measures Self-reported questionnaire, Anthropometric assessments by measurement. Blood glucose assessments.	intake, any psychosocial stress, and depression was higher in lower and middle educational occupational and socioeconomic groups. Fat intake/overweight and obesity was higher in higher socioeconomic groups. Alcohol intake was higher in higher educational group and middle occupational and socioeconomic status groups. Limitations Study was done in India Only people from urban area were included in the study
Anthony/ 2012	Adults AIs and Whites of 18-64 years of Age living in UK Randomly selected streets Power of 0.8 at p<.05	To compare physical activity levels, body mass index, habitual diet, tobacco use and prevalence of non-communicable disease between the two ethnic groups and to identify predictor	Cross-sectional study	ANOVA and logistic regression. Sample size for power of 0.80	Physical activity levels, BMI, habitual diet, tobacco use and prevalence of non-communicable disease Questionnaire	Relevant Findings Exercising 30 minutes a day and eating minimum five fruits and vegetable portions per day was positively related to education. Limitations Since the measures were self-reported the medical diagnoses may be inaccurate. Study was done in AI immigrants in UK.

		s for differences between groups.				
Daniel/2013	AI immigrants in Chicago Age 40-65yrs Sample size 110 with a power of 0.92	To describe lifestyle physical activity behavior of AI immigrants in Chicago.	Cross-sectional study	Chi-square and *t*-tests Bivariate Pearson correlation coefficients Regression analysis in four blocks	Current health assessed on a 5-point Likert scale Social influences measures included acculturation (20-item self-report measure), discrimination (Experiences of Discrimination (EOD) measure), and social support (PA Social Support Survey), Self-efficacy (17-item Self-Efficacy Scale), Physical activity behavior- (17 LTPA items survey)	<u>Relevant Findings</u> Educational level was positively correlated with physical activity ($p = .042$) Frequency of experiencing discrimination had a significant positive independent effect ($p = .007$) <u>Limitations</u> Cross sectional design has limitations in causal inference Convenient sampling makes findings not generalizable Self-reported questionnaire filled up by the investigator after participant responses in a group can cause social desirability bias.
Fleming/2008	5 AI (Gujrati Muslim) men in UK, age 55–72	To explore the influence of culture on (type 2)	Qualitative Case study	Topic and analytic coding	Past experiences and socio-economic factors	<u>Relevant Findings</u> Social atmosphere and cultural background lead to unhealthy dietary behaviors among participants.

	years with T2DM Convenient sampling	diabetes self-management in Gujarati Muslim men who reside in northwest England.	method Interview and participant observation		Embodied culture and dynamic culture Social and gendered roles Personal choice and contextual factors	<u>Limitations</u> This is a qualitative study so unable to generalize
Mukherjea/2013	AIs in the US aged 45 to 84 years. Convenient sampling	To examine the interconnections between health, food, and illness	Qualitative study using quasi-deductive approach Focus groups	Peer-debriefing process, emphasizing a conscious and collaborative approach to theme extraction	"Native" social and cultural understandings and influences of food-related behavior from India Intersection of "native" beliefs and American society and structures Reconciling conflicting interpretations about health risk	<u>Relevant findings</u> Impact of culture in healthy and unhealthy dietary pattern. Some believe that *karma* determines future and this affects whether they adopt healthy behavior or not Traditional celebrations frequently increase the unhealthy dietary habits <u>Limitations</u> Convenient sampling. Findings are not generalizable Over representation of Hindus
Shrivastava S./2014	339 adults in rural South India	To assess the prevalence and the determinants of T2DM in the rural population of Pondicherry.	Cross sectional descriptive study	t-test, chi-square, logistic regression model	Pretested behavior questionnaire for socio demographic assessment Physical assessment for height, weight, blood pressure Lab tests Lipid profile, post	<u>Relevant Findings</u> Relationship of socioeconomic status to T2DM was determined by physical activity and stress associated with the job. Physical inactivity, hypertension, smoking and alcohol abuse were significant risk factors associated with T2DM. <u>Limitations</u> Dietary assessment was done by single contact data.

					prandial blood sugar, Fasting blood glucose, HBA1C.	
Intermediary SDH and T2DM Prevalence						
Misra R/ 2018	1038 randomly selected AIs, aged 18 years and older, from seven US cities	To explore the relationship between the consumption of a traditional Asian Indian vegetarian diet and the prevalence of T2DM, obesity, and metabolic syndrome among AIs residing in the United States, after controlling for acculturation, dietary and lifestyle habits, family history of diabetes, knowledge of	Secondary data analysis of DIA study in 2010	Logistic regression analysis	Concepts 1. Demographic characteristics. (age, number of years in the US, gender, education, marital status, income, access to health care, self-rated health, English proficiency, and family history of diabetes) 2. Self-reported dietary behavior from nutrition subscale 3. Fasting capillary glucose (mg/dL) 4. Lifestyle factors (dietary habits, body mass index, spirituality, physical	Relevant Findings Consumption of fruits and vegetables reduced the risk of diabetes, vegetarian status reduced the risk of diabetes by 44% (OR = 0.55; 95% CI = 0.31, 0.99) but not the risk for obesity after controlling for demographic characteristics, lifestyle factors, and clinical factors. Limitations Self-reported and may include social desirability bias

		diabetes and CVD risk factors, and demographic characteristics			activity, and tobacco use) Measures Self-reported questionnaire, Fasting glucose test in the original study	
Ghai N.R. / 2012	Participants included 51,901 White non-Hispanic men and 602 AI men aged 45–69 years enrolled in the California Men's Health Study cohort. Convenient sampling	To compare lifestyle CVD risk factors between Asian Indian and White non- Hispanic men within categories of BMI	Cross sectional	Multivariable logistic regression, adjusting for demographics	Self-reported survey questionnaire that included lifestyle characteristics including diet, physical activity, alcohol intake, anthropometric measurements, and smoking.	Relevant Findings Fruit and vegetable intake are lower in healthy weight Asian Indians. Adj. Odds ratio, CI.68 (.52–.89) Lower moderate/vigorous physical activity compared to White non-Hispanics. Adj. Odds ratio, CI .35 (.27–.45) Asian Indians reported lower alcohol consumption (Adj. Odds ratio, CI 21 (.15–.29) and ever having smoked (Adj. Odds ratio, CI .57 (.34–.94) but current smokers were similar in both groups. Asian Indians reported higher levels of diabetes (20.4% vs 9.7%) compared to White non-Hispanics. Limitations Only men were included in the study which affects the generalizability No longitudinal report to assess any behavioral change.

						Questionnaire did not include dietary pattern and acculturation.
Gadgil/2014	150 AIs 45-84 years of age in San Francisco	To examine the associations of dietary patterns with components of the metabolic syndrome, lipid levels, hormones, cytokines produced by adipose tissue, and subcutaneous and visceral fat content in participants in the Metabolic syndrome and Atherosclerosis in South Asians Living in America (MASALA) pilot study	Cross-sectional study	Chi square and linear regression analyses	Data collected by researcher by using in person interview South Asian food frequency questionnaire. Weight measured using digital scale. Height-stadiometer WC-measuring tape X-ray absorptiometry.	<u>Relevant Findings</u> Adhering to the Vegetarian dietary pattern had lower fasting glucose (17.01 mg/dL; *p*=0.02) and HOMA IR (0.53mmol/L; *p*=0.02). No difference in diagnosis of diabetes or metabolic syndrome between those adhering to western or vegetarian dietary pattern. <u>Limitations</u> Pilot study Small sample size 6-month long study

Ram /2014	517 adult AI Men from Chennai, India with impaired glucose tolerance at baseline.	To examine the components of lifestyle intervention that are responsible for the reduced incidence of diabetes	Experimental study Random assignment of the subjects in the groups.	Chi square T test Univariate and multiple logistic regression analysis, Cox's proportional hazard model	Total energy intake and separate protein, carbohydrate and fat intake measured using visual basic programming tool administered by the researcher. Physical activity documented by scoring system (7-70) BMI	<u>Relevant Findings</u> Intervention group made more positive changes in lifestyle compared to the control group. Among the lifestyle goals, the protective Effect was the highest for reduced BMI (OR:0.15[95%CI:0.01–0.47]), followed by reduction in portion size (OR:0.39[95%CI:0.25–0.60]), reduction in oil intake OR:0.46 [95%CI:0.30–0.69]) and reduced consumption of carbohydrates (OR:0.52[95%CI:0.34–0.78]). Participants with increased lifestyle score were at reduced risk of developing diabetes (oddsratio:0.54[95%CI:0.44–0.67]; *p*<.001) Improved diet independent of physical activity reduced the incidence of T2DM <u>Limitations</u> 24-hour recall method that is used in the study is less accurate than the quantitative method of assessing the diet factors. Study was done in India not in the US
Kanaya/ 2010	150 adult AIs in the US Random sampling. Sampling frame South Asian surnames	To determine the prevalence and correlates of T2DM and prediabetes in AIs compared to other	Cross sectional study	Chi square test, ANOVA Proportional odds regression models,	Physical activity, smoking, alcohol medical history assessed through Self-reported questionnaires,	<u>Relevant findings</u> Lower energy intake from carbohydrates and higher protein intake was associated with more prevalence of diabetes. <u>Limitations</u> Small sample size. Study is cross sectional in nature.

		US ethnic groups.		Unadjusted, age adjusted, multivariate adjusted logistic regression models	clinical measurements done by the researchers to assess prevalence of T2DM	
Agrawal S./2012	AI adult women-99574 AI adult men-56744 from all states of India. The survey had 98% response rate	To describe the geographic variation in T2DM prevalence of and to examine the effect of modifiable risk factors on T2DM prevalence.	Cross-sectional study. Secondary data analysis of national health survey of 2005-2006	Descriptive statistics, Logistic regression analysis, odds ratio	Interviewer administered questionnaire with demographic, socioeconomic, and health content.	<u>Relevant findings</u> Age is most strongly associated risk factor with diabetes. People who watched television daily, had more intake of milk products, fish, and meat had higher prevalence of T2DM. Fruits and vegetable intake, smoking, or alcohol did not affect the prevalence of T2DM. <u>Limitations</u> This data is older >15 years.
Aravindalochanan V./2014	514 AI adults-Chennai, India	To assess whether prolonged sitting hours in work place predisposes individuals to risk of diabetes.	Cross-sectional study	Logistic regression	Biodemographic variables-Anthropometric measurements, random capillary blood glucose levels measured by researcher	<u>Relevant findings</u> Sitting more than 180 minutes a day increased random blood sugar levels. Higher blood pressure was a significant risk factor for T2DM. <u>Limitations</u> High random blood sugar, but not the diagnosis of T2DM was considered the outcome.

					for screening.	
Dhillon PK/2016	6367 AI adults 15-76 years in India	To evaluate the association between legume consumption, fasting glucose, and T2DM	Cross sectional study	ANOVA, F test, multilevel models and logistic analysis	Interviewer administered demographic and behavior questionnaire.	Relevant Findings There was no association between type 2 diabetes and legume consumption (relative risk (RR) (Q2) = 1·69; 95 % CI 0·86, 3·30, RR (Q3) =1·52; 95% CI 0·75, 3·09; RR (Q4)=1·68; 95% CI 0·76, 3·72). There was also no association between legume consumption and fasting sugar or insulin resistance. Limitations Study included teenagers from 15 years of age. Cross sectional study.
Ye.J / 2009	534 AIs in the US. Multistage sampling method with weighted sampling 77237 adults of US in the primary study.	To assess the prevalence of cardiovascular risk factors among AI, Philippino, Chinese, and other Asian populations in the US.	Secondary data analysis of NHIS 2003 - 2005.	Descriptive and bivariate analysis, Odds ratio adjusted for age, sex, education, marital status, and health status.	Self-reported survey data from computer assisted personal interviewing	Relevant findings AIs had highest prevalence of T2DM (OR= 2.27, 95% CI=1.63–3.20) than whites and other Asians. AIs had the highest prevalence of physical inactivity (OR = 1.50, 95% CI = 1.22–1.84). Limitations Data were self-reported. Data is >10 years old.
Vijayakumar/ 2019	869 adults >18 years in Kerala, India	To provide incidence estimates for T2DM	10-year prospective cohort study from 2007 with	Logistic regression analysis.	Anthropometric measurements, biochemical assessments measured during study. Interviewer administered	Relevant Findings T2DM incidence rate is 21.3% (95%CI=19.1-24.3. Age greater than 45 years, central obesity, overweight/obesity (BMI ≥ 25), family history of T2DM and hypertension showed strong association (*p* < 0.001) with the incidence of T2DM; physical inactivity

			follow up in 2017 with a response rate of 86.9.		questionnaire.	showed no significant association. <u>Limitations</u> Response rate is 68.7% Study was conducted in two locations in India.
Ghorpade /2013	1223 AI adults >25 years in rural Pondicherry, India	To assess the prevalence and risk factors of T2DM.	Population-based cohort study from 2007 with follow up on 2010 - 2011	Population estimates of the risk factors associated with T2DM were analyzed using the Generalized Estimating Equation model and the Population Attributable Risk (PAR) for T2DM calculated.	Interviewer administered questionnaire, Anthropometric measurements and fasting blood glucose measured during house visits.	<u>Relevant Findings</u> Incidence rate of T2DM 21.5/1000. The incidence was double among males (28.7/1000 PY; 95% confidence interval (CI): 21.0–38.7) compared with females (14.6/1000 PY; 95% CI: 9.4–21.7). Nearly half of the incidence was attributed to overweight/ obesity and alcohol use. <u>Limitations</u> Study was conducted locally in India.

Appendix 2

SAS codes for the study

Syntaxes developed for the study is provided below.

A. Syntax for separating AIs:

```
libname name xlsx “path";
data output table;
set input table;
If Mrace1=41;
Run;
```

B. Syntax for univariate analyses

```
/* Frequencies */
Proc Surveyfreq Data=dataset name;
Strata _Geostr;
Cluster _Psu;
Weight _Llcpwt;
Tables variables /Row Cv;
Run;
/* Means */
proc surveyfreq data=(dataset name);
strata STSTR ;
cluster psu ;
Weight _Llcpwt;
VAR variables;
run ;
```

C. Syntax for bivariate analyses

```
/* Chi Square Analysis-Wald Chi Sq*/
Proc Surveyfreq Data= dataset name;
Strata _Geostr;
Cluster _Psu;
Weight _Llcpwt;
```

```
Tables DV* IV;
/Row Chisq Cv;
Run;
```

D. Syntax for logistic regression

```
Proc Surveylogistic Data= dataset name;
Strata _Geostr;
Cluster _Psu;
Weight _Llcpwt;
Class DV IVs /Descending;
Model DV = IVs /  Rsq;
Run;
```

E. Mediation analysis

```
Proc Causalmed Data= data set name All;
Weight _Llcpwt;
Class DV IV mediator /descending;
Model DV  = IV mediator ;
Mediator mediator variable =IV;
Covar Age;
Run;
```

F. Multicollinearity test

```
Proc reg data= combined.combined5;
model DV=IVs /vif collin;
run;
```

Appendix 3. **Multicollinearity Tests**

A. Variance Inflation Factors of the Study Variables T2DM

Variable	**VIF**
Age	1.15680
Sex	1.03263
Income	1.14055
Home ownership	1.16320
Internet use	1.11045
Routine checkup in last 2 years	1.03742
Having a personal doctor	1.03742
BMI	1.03174
Alcohol consumption in last 30 days	1.09820
Smoked in last 100days	1.03863
Fruit frequency	1.13258
Other veg frequency	1.17593

B. Variance Inflation Factors of the Study Variables PDM

Variable	**VIF**
Age	1.17789
Sex	1.02286
Income	1.14659
Home ownership	1.21146
Internet use	1.10022
Health coverage	1.10936
Routine checkup in last 2 years	1.04274
Missing medical help due to cost in last year	1.07594
Having a personal doctor	1.05786
BMI	1.01006

C. Variance Inflation Factors of the Study Variables DS

Variable	**VIF**
Age	1.17789
Sex	1.02286
Income	1.14659
Home ownership	1.21146
Internet use	1.10022
Routine checkup in last 2 years	1.03742
Having a personal doctor	1.03742
BMI	1.01006
Smoked in last 100days	1.00087
Fruit frequency	1.12272
Other veg frequency	1.12201

Appendix 4

Links To BRFSS Survey Questionnaires

2013 survey questions

2014 survey questions

2015 survey questions

2016 survey questions

2017 survey questions

Appendix 5

Rutgers eIRB Approval Letter

RUTGERS eIRB

Arts & Sciences IRB - New Brunswick
335 George Street
Suite 3100, 3rd Floor
New Brunswick, NJ 08901
Phone: 732-235-2866

Health Sciences IRB - New Brunswick/Piscataway
335 George Street
Suite 3100, 3rd Floor
New Brunswick, NJ 08901
Phone: 732-235-9806

Health Sciences IRB - Newark
65 Bergen Street
Suite 511, 5th Floor
Newark, NJ 07107
Phone: 973-972-3608

DHHS Federal Wide Assurance Identifier: FWA00003913
IRB Chair Person: Cheryl Kennedy
IRB Director: Carlotta Rodriguez
Effective Date: 7/9/2019

eIRB Notice of IRB Determination

STUDY PROFILE

Study ID:	Pro2019001402
Title:	The impact of social determinants of health on the prevalence of type 2 diabetes among Asian Indian immigrants in the United States.

Principal Investigator:	Karen D'Alonzo	**Study Coordinator:**	Maya Joseph
Co-Investigator(s):	Rula Btoush Maya Joseph	**Review Type:**	Non-Human Determination

CURRENT SUBMISSION STATUS

Submission Type:	Request for Determination of Non-Human Subject Research (including Quality Assurance/Quality Improvement)	**Submission Status:**	Approved

Determination Date:	7/8/2019

The activities described in this application do not meet the regulatory definition of human subjects research provided in 45 CFR 46.102. Therefore, this project does not require approval by the IRB as submitted. Please note that changes to the project must be submitted to the IRB for review prior to implementation to determine if the changes incorporate elements of human subjects research activities which require IRB oversight.

ALL APPROVED INVESTIGATOR(S) MUST COMPLY WITH THE FOLLOWING:

1. Conduct the project as submitted to the IRB.
2. **Amendments/Modifications/Revisions**: If you wish to change any aspect of this project, you are required to obtain IRB review and approval prior to implementation of these changes unless necessary to eliminate apparent immediate hazards to subjects.
3. **Unanticipated Problems**: Unanticipated problems involving risk to subjects or others must be reported to the IRB Office (45 CFR 46, 21 CFR 312, 812) as required, in the appropriate time as specified in the attachment online at: https://orra.rutgers.edu/hspp
4. **Protocol Deviations and Violations**: Deviations/violations of the project must be reported to the IRB Office (45 CFR 46, 21 CFR 312, 812) as required, in the appropriate time as specified in the attachment online at: https://orra.rutgers.edu/hspp
5. **Completion of Study:** If your school requires, notify the IRB when your study has been stopped for any reason.
6. The Investigator(s) did not participate in the review, discussion, or vote of this protocol.

—

;tudy.PI Name:
;tudy.Co-Investigators:

Appendix 6

Rowan IRB approval letter

Rowan University

DHHS Federal Wide Assurance Identifier: **FWA00007111**
IRB Chair Person: Adarsh Gupta, DO
IRB Director: Sreekant Murthy
Effective Date: October 28, 2020

Notice of Approval

STUDY PROFILE

Study ID: PRO-2020-37
Title: The impact of social determinants of health on the diagnosis of type 2 diabetes mellitus among Asian Indians in the United States
Principal Investigator: Karen D'Alonzo
Study Coordinator: Maya Joseph
Co-Investigator(s): Maya Joseph

Sponsor: Department Funded
Approval Cycle: 12 Months
Risk Determination: Minimal
Review Type: Expedited
Expedited Category: 7. Research on individual or group characteristics or behavior (including, but not limited to, research on perception, cognition, motivation, identity, language, communication, cultural beliefs or practices, and social behavior) or research employing survey, interview, oral history, focus group, program evaluation, human factors evaluation, or quality assurance methodologies.

Study Approval Date: October 28, 2020
Study Expiration Date: October 27, 2021
Continuation Review Required: Yes

Records: 373
Protocol: version 10/19/2020
*** Study Performance Sites: Rutgers University School of Nursing, Newark, NJ**

CURRENT SUBMISSION STATUS

Submission Type: Initial
Submission Status: Approved
Submission Approval: October 28, 2020

ALL APPROVED INVESTIGATOR(S) MUST COMPLY WITH THE FOLLOWING:

1. Conduct the research in accordance with the protocol, applicable laws and regulations, and the principles of research ethics as set forth in the Belmont Report.
2a. Continuing Review: Approval is valid until the protocol expiration date shown above. To avoid lapses in approval, submit a continuation application at least eight weeks before the study expiration date.
2b. Progress Report: Approval is valid until the protocol expiration date shown above. To avoid lapses, an annual progress report is required at least 21 days prior to the expiration date.
3. Expiration of IRB Approval: If IRB approval expires, effective the date of expiration and until the continuing review approval is issued: All research activities must stop unless the IRB finds that it is in the best interest of individual subjects to continue. (This determination shall be based on a separate written request from the PI to the IRB.) No new subjects may be enrolled and no samples/charts/surveys may be collected, reviewed, and/or analyzed.
4. Amendments/Modifications/Revisions: If you wish to change any aspect of this study after the approval date mentioned in this letter, including but not limited to, study procedures, consent form(s), investigators, advertisements, the protocol document, investigator drug brochure, or accrual goals, you are required to obtain IRB review and approval prior to implementation of these changes unless necessary to eliminate apparent immediate hazards to subjects. This policy is also applicable to progress reports.
5. Unanticipated Problems: Unanticipated problems involving risk to subjects or others must be reported to the IRB Office
(45 CFR 46, 21 CFR 312, 812) as required, in the appropriate time as specified in the attachment online at: https://research.rowan.edu/officeofresearch/compliance/irb/index.html
6. Protocol Deviations and Violations: Deviations from/violations of the approved study protocol must be reported to the IRB Office (45 CFR 46, 21 CFR 312, 812) as required, in the appropriate time as specified in the attachment online at: https://research.rowan.edu/officeofresearch/compliance/irb/index.html
7. Consent/Assent: The IRB has reviewed and approved the consent and/or assent process, waiver and/or alteration described in this protocol as required by 45 CFR 46 and 21 CFR 50, 56, (if FDA regulated research). Only the versions of the documents included in the approved process may be used to document informed consent and/or assent of study subjects; each subject must receive a copy of the approved form(s); and a copy of each signed form must be filed in a secure place in the subject's medical/patient/research record.
8. Completion of Study: Notify the IRB when your study has been completed or stopped for any reason. Neither study closure by the sponsor nor the investigator removes the obligation for submission of timely continuing review application, progress report or final report.
9. The Investigator(s) did not participate in the review, discussion, or vote of this protocol.
10. Letter Comments: There are no additional comments.