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An Association of the Transgenerational Implications of Redlining and Obesity on Pediatric Type II Diabetes

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Walden University
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Abstract

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by

Carlin Dexter Nelson

MPH, The Medical University of South Carolina, 2020

BA, College of Charleston, 2018

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

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Abstract

As the prevalence and incidence of childhood obesity has increased, so has the number of cases of pediatric Type 2 diabetes mellitus (T2DM). Although made unconstitutional in 1968, the transgenerational implications of redlining can be observed in disinvestments resulting in neighborhood detraction. Utilizing the 2019–2020 National Children's Health Survey, the purpose of the study was to evaluate the relationship between obesity, T2DM, and neighborhood detraction elements as well as assessed indicators of T2DM in non-institutionalized children 6 through17 years of age (*N* = 34,725). The social determinants of health perspective served as the conceptual framework for the study. Results indicated that the presence of detracting neighborhood elements was strongly associated with food insecurity and perceived safety. Binary logistic regression analyses, controlling for sex, age, and race/ethnicity, showed a 23% (*OR* = 1.230; 95% CI, 1.151-1.315), 34.8% (*OR* = 1.348; 95% CI, 1.209-1.505), and 48.5% (*OR* = 1.485; 95% CI, 1.300-1.696) increase in odds of obesity in respondents who live in areas with one, two, and all three detracting elements, respectively. Controlling for the same variables and socioeconomic status, there was a 90.4% (*OR* = 1.904; 95% CI, 1.203-3.016) and 80.5% (*OR* = 1.805; 95 CI, 1.017-3.203) increase in odds of T2DM among those who resided in a neighborhood with two and all three detracting neighborhood elements, respectively. Predictors of T2DM were overweight/obese BMI, 12–17 years old, living with grandparents, food insecure, and living in a neighborhood with the presence of two detracting elements. Implications for positive social change include understanding the relationship between location, policy and health outcomes that can foster health equity and social justice.

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Dedication

First, giving all glory and honor to my Heavenly Father. I would like to give thanks for giving me the capacity, opportunity and strength to achieve one of my many life's goals. This dissertation is dedicated to my mother, Kimberly H. Bass and my entire family. As the unseen hands of my brilliance, I want to extend an unfathomable amount of gratitude for providing me the necessary tools and support to go through this entire process. Even when there were times that I was least motivated, you fed my spirit, built my confidence and recharged my intrinsic motivation. To my mother, thank you for the many sacrifices that you have endured for me to get to this point. While we may not have always had everything, you have instilled in me values that cannot be assigned a monetary cost. I pray that I have made you proud as I continue to grow into a man of ideals, substance, acceptance and love. Additionally, I would like dedicate this dissertation to TRIO programs everywhere. These programs but specifically the College of Charleston's Upward Bound program provided me with the emotional and academic tools that I needed to succeed as a first-generation student. I am eternally grateful for the exposure to activities, culture and places that I would have never imagined that I, an African American boy who attended Title I schools would have experienced. Lastly, I would like to dedicate this dissertation to every student and alumni of Burke High School in Charleston, South Carolina. We may be expected to run the same race with our counterparts while only having a quarter of the tools; it may be frustrating but you too can achieve anything you want in life. We are resilient because of our circumstances, but our circumstances do not have to be permanent.

Acknowledgments

I would not have been able to reach this amazing milestone without some very important people in my life. First, I would like to thank my dissertation chair, Dr. Jamuir M. Robinson for your grace, leadership, guidance, knowledge, and patience throughout this process. I am forever grateful for your candor, mentorship and willingness to talk through things; because of you not only am I shaping into a better epidemiologist but aspiring faculty member and mentor for the next generation of public health practitioners. Thank you to my other committee members, Dr. Simone W. Salandy and Dr. Sanggon Nam for your comments and feedback.

Additionally, I would like to acknowledge my immediate circle of friends who secure my safety net when I did not always feel adequate. Because of Shanice Nelson, Maurice Bass, Keon Nelson, Franchell Smalls-Lewis, Rita V. Bass, Vermell Brewer-Bass, Dexter and Regina Nelson, Bryce and Lillie Nelson, Ashley Glenn Robinson, Dayana and Cynthia Wilkins, Shaylyn McKinney, Joshua Bryan, Joequise Wright, Lawrence Hickson, Jordan Wiggins, Ja'Von Scott, Albertus Cocklin, III, Gabrielle Hollinshead, Merrill Gadsen, Ricardo Robinson, Jacqueline Sanders, and Albert Schuler, I was always surrounded by love, reassurance and support. You all continuously create a safe space for me to be vulnerable while also reminding me who I am, and whose I am. None of you will ever know what your support, visibility and love mean to me.

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Chapter 1: Introduction to the Study

This quantitative cross-sectional secondary data analysis was conducted to explore the predictors of pediatric Type 2 diabetes mellitus (T2DM) and if the prevalence of pediatric T2DM and the prevalence of pediatric obesity is associated with detracted neighborhood elements. There has been a significant increase in youth not only being diagnosed with T2DM but being diagnosed as overweight or obese. Though there are many risk factors that influence susceptibility and severity of T2DM and obesity, some of those risk factors are structurally influenced by the disinvestments of neighborhoods and communities (Green et al., 2017). By assessing the interconnection between location, policy, and health outcomes, public health professionals are able to execute the three core functions of public health in creating health equity among a vulnerable population—youth and young adults.

This chapter provides background information about T2DM, obesity, and detracted neighborhood elements as a possible result of redlining. It also illustrates the public health problem, conveys the research questions and hypotheses, reports the justification of the theoretical framework and nature of the study, provides definitions of terms, and discusses the assumptions, scope, delimitations, and limitations. Lastly, this chapter presents the significance of this study to the existing literature and field.

Background

Obesity impacts 39 million children under the age of 5 worldwide (World Health Organization [WHO], 2020). In 2016 the global prevalence rate for childhood obesity and overweightness among children 5–19 was 18% (WHO, 2020). From 2017–2020 in the

United States, obesity prevalence among children and adolescents 2–5, 6–11, and 12–19 years were 12.7%, 20.7%, and 22.2%, respectively (Stierman et al., 2021). Though being considered a preventable chronic but reversible condition, there are many disparities observed in childhood obesity and overweightness including but not limited to race/ethnicity, sex, habitancy, gender expression, and socioeconomic status (SES; Azagaba et al., 2019; De Lorenzo et al., 2020; Fradkin et al., 2015; Zou et al., 2021).

Obesity is a contributing factor to increased risk of T2DM; when compared to children with normal body mass index (BMI), obese children have a quadrupled increased risk of having T2DM (Abbasi et al., 2017). T2DM is diagnosed when the body does not know how to properly use or process glucose (American Diabetes Association [ADA], 2009). T2DM can be influenced by genetics, environment, behavior, social, and structural factors that can not only impact insulin resistance but obesogenic factors (Wondmkun, 2020). Earlier literature suggested that because obesity had a presumable causal relationship with T2DM that it was solely etiologic, but new research suggests that there may be an ambi-directional relationship between these two associated diseases (Chobot et al., 2018). Most of the literature indicates that this relationship may be impacted by environment (County Health Rankings & Roadmaps, 2017; Lee et al., 2015).

Redlining is the discriminatory practice of denying or limiting services to specific areas (Winling &Michney, 2021). Based on racist ideologies, the practice of redlining created zones based on who the banks decided to be risky investments (Winling & Michney, 2021). This practice created zones that were color categorized as Grade A = Good (green), Grade B = Still Desirable (blue), Grade C = Definitely Denying (yellow), and Grade D = Hazardous (red; Winling & Michney, 2021). These color and graded zones were placed on maps created by the Homeowners Loan Corporation (HOLC) and used in many banks (Wipling & Michney, 2021). Although it primarily impacted Blacks/African Americans, any race/ethnicity that could not identify as White, Anglo-Saxon and Protestant were subjected to its discriminatory practices (Brown, 2021). Not investing in what is deemed a risky environment shaped disadvantaged environments, which often impacts health outcomes through multiple pathways (Ellison, 2018).

Neighborhood detraction affects historically redlined areas with the most common forms of detraction as hyper-vacancy (Capps & Mock, 2019). Hyper-vacancy is defined as, "a condition in which vacant properties are so extensive and centralized that they define the character of the entire area" (Padcrush, n.d., para. 1). The impact of redlining differs from city to city, but the intent and the results are similar (Jan, 2021). Compared to areas that have not been redlined, redlined areas have 5-10% more vacant homes (Appel et al., 2016; Meier & Mitchell, 2022). Redlined areas are often described as socially disadvantaged because of the disinvestments, which often result in poorer infrastructure, more vacant houses, and impacted SDOH (McCullough, 2022). These underserved areas are often associated with poverty, high crime rates, food insecurity, and a lack of resources that increase obesogenic and diabetes risk factors (Powell, 2021).

Although there is evidence on neighborhood characteristics and health outcomes like obesity and T2DM, there are limited studies that aim to evaluate the relationship between potential consequences of redlining and pediatric health outcomes, specifically obesity and T2DM. Additionally, there are no studies presented in the literature using proxy variables as a substitute for redlining such as the presence of detracting neighborhood elements. This study is needed because the implications of redlining are transgenerational and although illegal, still impacting and covertly occurring in cities today (Best & Mejia, 2022). This study brings attention to social justice and health equity by addressing the structural challenges that may influence unhealthy lifestyles, choices, and outcomes.

Problem Statement

Once considered an adult disease, T2DM is being observed more in young children and adolescents than before (Lawrence et al., 2021). Although T2DM affects 6.28% of the world's population, according to the ADA, 0.35% of the U.S. population under the age of 20 have been diagnosed with T2DM (ADA, 2022; Khan et al., 2020). Children are a vulnerable group because they are dependent on others for their needs. It was posited that the environment accounts for 10% variation in health outcomes including but not limited to expenditures, outcomes, morbidity, and mortality (County Health Rankings & Roadmaps, 2017). Although there have been many studies to look at the impact that redlining may have on health outcomes, there are no studies investigating neighborhood detraction and its potential influence on the susceptibility of obesogenic risk factors on T2DM in the pediatric population across many U.S. metropolitan cities simultaneously.

Purpose of Study

The purpose of this quantitative study was to evaluate if both T2DM and obesity in the pediatric population are associated with the presence of detracted neighborhood elements as well as examining the influence of demographic (sex, age race/ethnicity, socioeconomic status and family structure), environmental (food insecurity, accessible playgrounds and parks, safe neighborhoods, safe walking paths, accessible recreation centers and presence of detracting neighborhood elements), physical activity, and BMI on the prevalence of T2DM. These explorations were answered with three research questions.

Research Questions and Hypotheses

RQ 1: What is the association between obesity and detracted neighborhood elements in the pediatric population when controlling for age, race/ethnicity, sex, and socioeconomic status?

H_a1: There will be an association between obesity and detracted neighborhood elements when controlling for age, race/ethnicity, sex, and socioeconomic status?

H_01: There will be no association between obesity and detracted neighborhood elements when controlling for age, race/ethnicity, sex, and socioeconomic status?

RQ 2: What is the association between T2DM and detracted neighborhood elements y in the pediatric population when controlling for race/ethnicity, sex, and socioeconomic status?

H_a2: There will be an association T2DM and detracted neighborhood elements when controlling for race/ethnicity, sex, and socioeconomic status?

H_02: There will be an association T2DM and detracted neighborhood elements when controlling for race/ethnicity, sex, and socioeconomic status?

RQ 3: Do demographic characteristics (sex, age, race/ethnicity, socioeconomic status, and family structure), environmental (food insecurity, accessible playgrounds and parks, safe neighborhoods, safe walking paths, accessible recreation centers and presence of detracting neighborhood elements), physical activity, and BMI have an influence on the prevalence of type 2 diabetes among the pediatric population?

H_a3: Demographic (sex, age, race/ethnicity, socioeconomic status, and family structure), environmental (food insecurity, accessible playgrounds and parks, safe neighborhoods, safe walking paths, accessible recreation centers and presence of detracting neighborhood elements), physical activity, and BMI have an influence on the prevalence of type 2 diabetes among the U.S. pediatric population.

H_03: Demographic (sex, age, race/ethnicity, socioeconomic status and family structure,), environmental (food insecurity, accessible playgrounds and parks, safe neighborhoods, safe walking paths, accessible recreation centers and presence of detracting neighborhood elements), physical activity, and BMI do not have an influence on the prevalence of type 2 diabetes among the U.S. pediatric population.

Theoretical Framework

In America, public health systems were popularized during the industrial revolution where famine, poverty, and infectious diseases were high (Karamanou et al., 2012). Although there have been many theories on how diseases and pathogens were caused (e.g., miasmas) as conditions worsen, scientists and epidemiologists began looking at social conditions (Karamanou et al., 2012). The theoretical framework used for this analysis was the social determinants of health (SDOH). Although there is evidence that this theoretical framework may have been utilized earlier (i.e., John Snow and

Cholera or Rudolf Virchow and Typhus), the credit is often assigned to the 1967 UK Whitehall study (Osmick & Wilson, 2020). This framework attempts to describe the often overlapping and intersectional social conditions that describe the environment where person/persons are born, live, learn, work, play, worship, and age (Artiga & Hinton, 2019). Additionally, this framework posits that these social conditions influence health outcomes and expenditures (Centers for Disease Control and Prevention [CDC], 2020). As shown in Figure 1, these conditions are often grouped into five domains: economic stability, health care and quality, education access and quality, neighborhood and built environment and social and community context (CDC, 2020).

Figure 1

Social Determinants of Health Frameworks Constructs

Note. From "Social Determinants of Health," by CDC, 2021 (https://www.cdc.gov/visionhealth/determinants/index.html)

This theoretical framework relates to the study's research questions because it aims to evaluate the influence that social conditions from each domain has on the obesogenic risk factors on T2DM in the pediatric population. Additionally, this study focuses on the intersectional and overlapping contribution that each domain may have upon one another which may increase or attenuate susceptibility and severity of health risks and outcomes.

Nature of the Study

This quantitative cross-sectional secondary data analysis used data from the cross-sectional National Children Health Survey (NCHS). This dataset was utilized to investigate if the presence of detracting neighborhood elements perpetuated pediatric obesity, and pediatric T2DM. To address the three aims of this analysis, logistic regressions (binomial and ordinal) were conducted to control for a combination of covariates: demographic (sex, age, race/ethnicity, socioeconomic status, and family structure), environmental (food insecurity, accessible playgrounds and parks, safe neighborhoods, safe walking paths, accessible recreation centers and presence of detracting neighborhood elements), physical activity, and BMI. In addition to the logistic regressions conducted, a chi square (X^2) test of independence was performed among all the variables and presence of neighborhood detraction elements. A combination of odd ratios (ORs) adjusted odds ratios (aORs), 95% confidence intervals (95% CI), and *p*-values were used to interpret the analysis.

Definitions of Key Terms

The key terms that were used in this research study are based on variables from the data collected in the NCHS and throughout the literature.

Accessible playgrounds and parks: Refer to the availability and proximity of playground and parks near households (Molina-García et al., 2021).

Accessible recreation centers: The presence/accessibility of recreational facilities located near the neighborhood/community (Andrade et al., 2021).

Body mass index (BMI): An anthropometric measure calculated as a ratio of height (meters) and weight (kilograms) that is clinically used to estimate body fat. In children, BMI is age and sex specific that compares the same age and sex of a child to the reference population of that same age and sex (CDC, 2021; Nuttall, 2015).

Family structure: The combination of relationships shared by a group of individuals who are related by birth, adoption, fictive kin, marriage who reside in one household (Health Resources & Services Administration [HRSA], n.d.).

Food insecurity: A social determinant of health that is captured by economic and social factors that describes limited, unreliable or no access to adequate, affordable, and nutritious food (U.S. Department of Agriculture, Economic Research Service, n.d.).

Overweight/Obesity: The excessive accumulation of adipocytes (fat cells); clinically diagnosed in children with BMI reported in the 85^{th} -95^{th} percentile and greater than the 95^{th} percentile, respectively (CDC, 2021).

Physical Activity: “any bodily movement produced by skeletal muscles that require energy expenditure” (WHO, n.d., para 1).

Presence of detraction neighborhood elements: Refers to the presence of littering, abandoned buildings, graffiti and vandalism (Cronin & Gran, 2018).

Race/Ethnicity: Social constructs used to divide a population into groups based on physical features/characteristics and culture expressed in a given geographic region

(Flanagin et al., 2021).

Redlining: A discriminatory policy institutionalized by the HOLC that denied services and investments to areas deemed financially risky. The term "redlining" refers to the color given to those "hazardous" areas on maps that predominantly impacted minorities (Winling & Michney, 2021).

Safe neighborhood: Perception of not being fearful around the neighborhood/community one lives/resides/visits (Sun et al., 2012).

Safe walking paths: measures safe access and availability of sidewalks and walking paths present in the neighborhood/community *(*Gwam et al., 2022*)*.

Socioeconomic status (SES): The percentage of household income relative to the federal poverty level (FPL), a function of household income, and number of people in that household compared to a threshold amount that qualifies for governmental programs (Berzofsky et al., 2014).

Type 2 diabetes mellitus (T2DM): T2DM is a condition that results in hyperglycemia which can cause blood and erythrocytes (red blood cells) to change their consistency; potentially resulting in physiological abnormalities and interruptions (ADA, 2009).

Assumptions

Since this study is a secondary data analysis collected from a survey where the parent/parents answer health questions about their child, I assumed they were willing respondents. In addition, I assumed the respondents of the NCHS were comfortable with honestly self-reporting the information asked in the survey. Answering honestly and with completeness assist the agencies responsible for this survey report the general health status of U.S., non-institutionalized children aged 0–17.

A major assumption of this analysis was that redlining is still being experienced across the nation. Although outlawed in 1968, not only is redlining still occurring covertly, but the impacts of redlining are also still affecting metropolitan cities (Best & Mejia, 2022; Perry & Harshberger, 2019). According to studies, 74–75% of cities historically redlined but specifically assigned the Grade of D four decades ago can be considered low to moderate income today (Columbia Broadcasting Services, 2020; Jan, 2021). An additional assumption was that areas that were reported as detracted are potentially related to areas that were historically redlined. Lastly, I assumed that because this a nationally representative sample, that all social categorizations (age, race/ethnicity, sex/gender, sexual orientation, ableism etc.) are represented in the sample. Though the sample of these often-overlapping social categorizations may differ by location, it is important they are included for generalizability.

Scope and Delimitations

This quantitative cross-sectional secondary data analysis addressed the relationship of detracted neighborhood elements with the prevalence of pediatric obesity and pediatric T2DM from a cross sectional nationally representative sample consisting of non-institutionalized children 0–17 years old. Additionally, I evaluated predictors in the prevalence of pediatric T2DM in the same sample of children. Through address sampling, the only children included in this study are those who responded completely to the survey. Collecting responses from only children who reside in a residence makes this generalizable among similar audiences.

Limitations

Similar to other studies, no study is without imperfections presented as limitations. First, a secondary dataset was used from fixed questions in a survey. This circumstance excludes other variables of interest that were not present or available in the dataset. For example, in this secondary dataset for confidentiality purposes, redlining zones as determined by the 1930s HOLC map was not available, so a proxy variable (the presence of detracted neighborhood elements) was used. Redlining is not always accessible or feasible because in some cities, HOLC maps cannot be found and to measure redlining requires access to confidential information or census tract level data. Although highly unlikely to differ, this proxy variable was the most feasible variable to infer the implications of historical redlining. Second, the data collected in the NCHS are self-reported by parents who live in a residence which may result in recall, misclassification, and selection bias. Only capturing information from parents who reside in a home excludes the 33.3% of families that are experiencing homelessness (World Population Review, n.d.). Lastly, this analysis was conducted as cross-sectional. Cross-sectional research designs are not able to determine temporality.

Significance of Study

This study contributes to the field of public health because it not only applies the SDOH as a framework (presented through associated variables) but how those often overlapping and intersectional social conditions can be impacted by location/geographic region, which can impact health outcomes. To my knowledge this is the first study that used a nationally representative dataset measuring children's health to examine the relationship between policy (redlining), environment (the presence of neighborhood detraction), and health outcomes (obesity and T2DM). Additionally, this was the first study on impact of redlining via neighborhood detraction and the nexus to health outcomes in a vulnerable population. In real-time, this study upheld the three public health core functions—assessment, policy development, and assurance.

The findings of this study could provide evidence to all stakeholders about where to place appropriate funding to improve detracted neighborhoods, and provide the needed resources that promote a healthy, safe, and active lifestyle. Additionally, these findings could be used to make constituents of these major cities aware of legislatures that may or may not have their best interest. Further, these findings can be used to create evidence based, data driven policies focused on sustainable interventions that promote health equity and social justice. Creating these policies and initiatives allows communities/neighborhoods to flourish, and it influences healthy behaviors and ideologies among the younger generations who eventually become the primary contributors of the economy.

Summary

The prevalence of obesity and T2DM has increased in youth and young adults. Both of these chronic but reversible conditions are influenced by a plethora of factors that may differ by race/ethnicity, SES, and sex/gender. Neighborhood and built environment are one of these factors. Redlining was a discriminatory policy that structurally forced minorities into geographic areas, rendered those areas as hazardous, thus risky investments. The disinvestment of these neighborhoods resulted in neighborhood detraction, which may promote obesogenic and T2DM risk factors. Though made illegal in 1968, the impact of redlining is still present. Using detracted neighborhood elements provides insight on the potential effects of redlining. I explored the relationship between neighborhood detraction with the prevalence of T2DM and obesity as well as the influences of T2DM in a nationally representative sample of non-institutionalized children aged 0–17 years. In Chapter 2, the impact of the effects of redlining on obesity and T2DM on a national level are examined, identifying a gap in the research. These findings highlight the affect that both the social and political determinants of health have on health outcomes in hopes that stake holders and legislators can jointly participate in creating health equity and social justice.

Chapter 2: Literature Review

The purpose of this quantitative research study determined whether there was a relationship between policy, environment, and health outcomes. Specifically, I investigated if the presence of detracted neighborhood elements was associated with obesity on T2DM among the pediatric population. While there is evidence in predictors/relationship of obesogenic factors on T2DM, and the impact that the environment can have on health outcomes, there is a lack of information investigating those relationships in the pediatric population. Additionally, there is a lack of evidence assessing redlining's current influence on pediatric health outcomes, specifically obesity and T2DM. This chapter discusses the etiology and epidemiology of both pediatric obesity and pediatric T2DM, the relationship between obesity and T2DM, the transgenerational implications of redlining, and its influence on obesogenic and T2DM risk factors among the pediatric population, and the SDOH.

Literature Search Strategy

The literature review was obtained with a list of keywords used to identify the research studies covered within this chapter: *type 2 diabetes, healthcare expenditures, pediatrics, epidemiology, risk factors, dose-response, longitudinal, etiology, prevention, obesity, obesogenic, child adiposity, environment, disparities, blight, hypervacancy ,social determinants of health, SDOH, neighborhood, built environment, racism, redlining, residential apartheid, health outcomes,* and *policy*. Electronic databases included American Journal of Epidemiology, American Academy of Pediatrics, PUBMED, Pediatric Obesity, Diabetes, MEDLINE, SAGE Journals, Science Direct, APA PsychInfo, and search engines such as Google Scholar. Further, the Walden University's library was used to find some full text of these articles. I also searched for publications that were used as references of the articles I initially found.

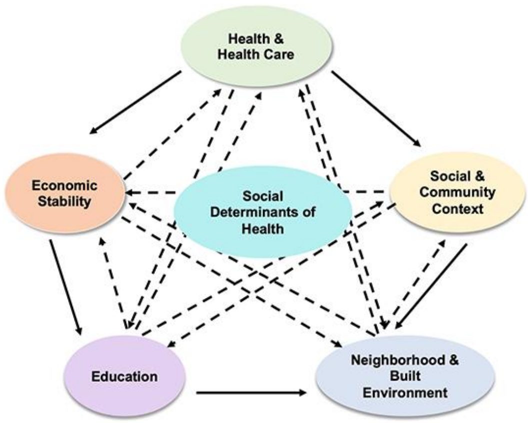
The initial criteria of the literature review consisted of only scholarly peer-reviewed articles published between 2018 and 2022; however, there were some utilized sources published more than 5 years ago. Additionally, there was a small percentage of publications that were not peer-reviewed such as well-known magazines or newspapers used in this literature review because of the lack of current peer-reviewed empirical evidence investigating the relationship between neighborhood detraction, obesity and T2DM in the pediatric population. The literature review not only provided relevant background information, it provided an opportunity to establish a gap in the literature between policy, location, and health outcomes in a vulnerable population.

Theoretical Framework

As shown in Figure 2, SDOH are non-medical, often overlapping and intersecting social conditions that aim to describe how economic stability, health care and quality, education access and quality, social and community context, and neighborhood and built environment influence health outcomes expenditures and disparities (WHO, n.d.; CDC, 2020; Hills-Briggs et al., 2020)].

Figure 2

Intersectional Relationship Among the Social Determinants of Health



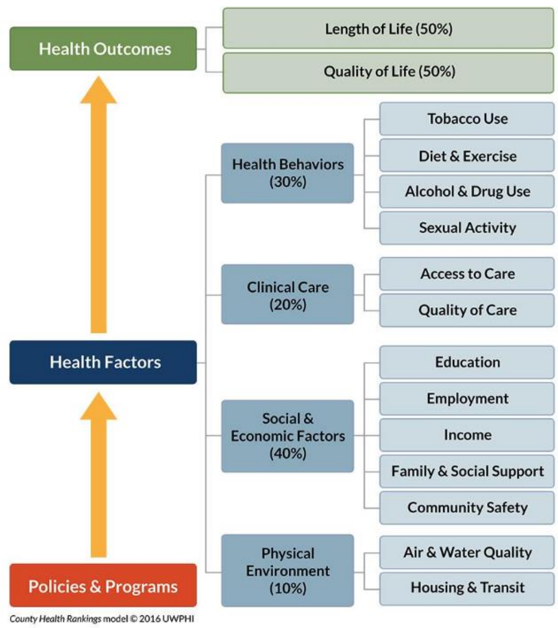
Note. From "Impact of Social Determinants of Health on the Emerging COVID-19 Pandemic in the United States," by K. Pandey, 2020, *Frontiers in Public Health,* 8, p. 406. https://doi.org/10.3389/fpubh.2020.00406

Under the domain of economic stability, social conditions, and factors such as employment, income, and debt are considered because the type of job one works influences the income they earn and benefits they are able to utilize (health insurance, paid sick leave, parental leave etc.; Singu et al., 2020). Health care and quality includes health coverages, access, provider and treatment/intervention availability, quality of care, as well as cultural and linguistic competency (CDC, 2020). Education is a domain that entails literacy, higher education, vocational training, and language (CDC, 2020; Drake & Rudowitz,2022; Singu et al., 2020). The fourth domain, social and community context, focuses on support systems, safety concerns, stress, discrimination/prejudice, policing, cohesion, and engagement (Office of Disease Prevention and Health Promotion, n.d.).

Lastly, neighborhood and built environment attempts to describe the environment through conditions such as walkability, availability of green spaces and recreation centers, transportation, housing, food insecurity, and air/water quality (CDC,2020; Singu et al., 2020). Though each of these things could influence one another, as shown in Figure 3, some domains may hold more weight in the pathogenesis of chronic diseases such as T2DM or obesity.

Figure 3

County Health Rankings and Roadmaps



Note. From "Interaction Between Health Outcomes, the SDOH, and Policies and Programs," n.d. (https://www.countyhealthrankings.org/resources/county-health-rankings-model). Public domain.

Often credited as the first study to investigate social conditions and health outcomes is the 1967 UK White Hall study (Osmick & Wilson, 2020). This study was on the association between social class, and health status; after a 10 year follow up, this study conveyed an inverse relationship between social class and self-reported health status (Osmick & Wilson, 2020). As a primary concept in public health, this theory is often in some form applied in many studies, but in its entirety, literature is scarce, inconclusive, and even greater scarcity amongst children and young adults (Stangvaltaite-Mouhat et al., 2021). However, to measure all SDOH domains, Javed et al. (2022) created a social disadvantaged score utilizing the adult population of the 2013-2017 National Health Interview Survey (NHIS). This score was created through the combination of SDOH indicators and being socially disadvantaged was represented by a higher combined SDOH score. Javed et al. discovered that when compared to those with lower cumulative SDOH scores, those with higher combined SDOH scores were associated with normal weight ($18.5 \leq \text{BMI} < 25$), overweight ($25 \leq \text{BMI} < 30$), obesity classes 1-2 ($30 \leq \text{BMI} < 40$) and obesity class 3 ($\text{BMI} \geq 40$) by 15%, 50% and 70% increase in obesity prevalence, respectively.

Social disadvantages and SDOH interact in public health and health care pathways that influence health outcomes (Fradkin et al., 2015; Schillinger, 2020). Social disadvantages tend to be inherited and have been shown to be positively correlated with increased later life BMI (Lowry,2020). Social disadvantages linked with childhood obesity are younger children, single parent households, and disadvantaged neighborhoods (Yusuf et al., 2020). The most consistent upstream social determinant of health predictor of all health outcomes including T2DM and obesity is SES (Hill-Briggs et al., 2020; Lakerveld & Mackenbach, 2017; Lowry et al., 2020; Sawchuck, 2019; Yusuf et al., 2020). Similarly, the findings of social disadvantages based on the social determinants of health were found to be associated with T2DM (Hills-Briggs et al.,2020). The prevalence of T2DM is associated with social gradient (Hill et al.,2013). Most of the literature has focused on adults but since SDOH and social disadvantages can be inherited, and temporary, most of the social conditions can be applied to children. Similar to obesity, SES is a strong predictor of T2DM because it is linked to almost all SDOH (Wang & Geng,2019). In self-management of T2DM, the most important SDOH include economic stability, education, health care, social and community support and built environment (Clark & Utz,2014). The upstream social determinants of health and downstream effects differ amongst the socially disadvantaged and influences the prevalence, incidence of T2DM as well as health disparities (Brady et al., 2021).

Literature Review Related to Key Variables

Etiology of Pediatric Obesity

Pediatric obesity is defined as the excessive accumulation of adipocytes or fat cells in a child (Kumar & Kelly, 2017). While it can be a complex interaction, when a person consumes more calories than their body is able to metabolize, the excess calories are converted into adipocytes (Lin & Li, 2021). Although it has been criticized within the past decade, obesity is clinically defined/assessed by the BMI, a ratio of weight to height (CDC, 2011). BMI is reported as a quotient that aims to characterize severity of obesity by categorizing the reported result into one of the four acknowledged percentiles (CDC, 2021). The four cut off points signify weight status: underweight (less than the 5^{th} percentile), healthy weight (5^{th} percentile to less than the 85^{th} percentile), overweight

(85th to less than the 95th percentile), and obese (equal to or greater than the 95th percentile; CDC, 2011). Unlike BMI with adults, using this anthropometric measurement with children differs in interpretation with the percentiles because it is sex and age specific. For example, a 10-year-old boy who has a BMI of 23, would be placed in the obese category and it would be interpreted as, he has a weight greater than 95% to other boys who are also 10.

Childhood obesity is often considered to be a genetic, structural, behavioral, environmental, social, and economic influenced condition with well documented health disparities (Lee et al., 2019; Mackey et al., 2022). Although there are many causes of childhood obesity such as genetics, environment, stress, health conditions, medications, and poor sleep, the most common two are poor diet and living a sedentary lifestyle (Balentine, 2015; CDC, 2012; Lin & Li, 2021; National Heart, Lung and Blood Institute, 2012). The Western diet that mostly consist of foods/drinks high in salt/sodium, sugar, and fat not only have many calories in small amounts for cheap prices but are associated with the exponential increase of obesity in the United States (Rakhra et al., 2020). In a systematic review assessing dietary patterns and childhood obesity, it was reported that there was a 2% to 255% increase in risk in childhood obesity depending on the established obesogenic food group (Liberali et al., 2020).

The second most common cause of childhood obesity is a lack of physical activity or living a sedentary lifestyle (Balentine, 2015; CDC, 2012; Hong et al., 2016). Participating in physical activity allows the body to use the energy that has been consumed and stored, which could decrease visceral obesity and waist circumference

(Ando et al., 2020). Physical activity is important in the prevention and reduction of childhood obesity because the amount of energy that children use for basic biological/physical processes are 25–35% (Ponnambalam et al., 2022). The National Health and Nutrition Examination Survey (NHANES) used a nationally representative sample to report that physical activity was a protective risk factor for obesity in children (Hong et al., 2016). Acknowledging children's energy expenditure and the physical and psychosocial health benefits of physical activity, the CDC recommends 60 minutes per day for children 5–17 years old (Thalken et al., 2021).

Due to access barriers and funding there are also disparities among obesity rates in children and playground quality and availability (McCarthy et al., 2017). Another cause of obesity is environment (Balentine, 2015; CDC, 2012). In 2014, Roeder determined that the best indicator of health was the zip code because it captures the SDOH. Environment is included in the SDOH in a domain entitled neighborhood and built environment (CDC, 2020). This domain has a goal of creating and maintaining neighborhoods and environments that promote a healthy lifestyle and often considers things like walkability, crime, access to fresh affordable foods, parks/recreation centers (CDC, 2020). Many studies have investigated the association between environmental factors such as crime, food deserts, lack of infrastructure and obesity (Rundle et al., 2009; Sugalia et al., 2016; Wei et al., 2021). In neighborhoods that were perceived as not safe there was 123% increase in odds of childhood obesity when compared to children who did not perceive their community as dangerous (Reis et al., 2020). Often interconnected with other social categorizations such as age, SES, urbanity, race/ethnicity, and built environment has been considered a component in the childhood obesity epidemic (Reis et al., 2020).

A fourth cause of obesity is genetics (Balentine, 2015; CDC, 2012). The root of the epigenetic mechanism of the heritability of obesity has been compartmentalized to monogenic (one gene), polygenic (many genes), and syndromic (chromosomal rearrangement; Tirthani et al., 2022). Studies inquiring about heritability of obesity in families, twins, and populations reported that 40%–70% of transgenerational obesity could be explained by genetics (El-Sayed et al., 2013; Hebebrand& Hinney, 2009; McPherson, 2007). Racial/ethnic differentiation has also been reported as risk factor in the type of heritability (El-Sayed et al., 2013). Although monogenic obesity has been linked with the variation of the MC4R gene, which is associated with hyperphagia (over-eating), it and syndromic obese heritability are rare, whereas polygenic obesity is the most common form and is often exacerbated by behavioral factors (Huvenne et al., 2016). The overlapping impact of these causes can describe both susceptibility and severity of obesity (McPherson, 2007).

Further, stress has a causal relationship with obesity (Balentine, 2015; CDC, 2012). Stress is often described as the body's response to a non-homeostasis state (Charmandari et al., 2005). Stress produces the stress hormone known as cortisol (Charmandari et al., 2005; van der Valk et al., 2018). The positive feedback loop mechanism between cortisol and overweightness/obesity consists of the higher the amounts of cortisol produced, the higher energy expenditure, and the increase in appetite (van der Valk et al., 2018). Though stress/stressors maybe inescapable, there are vulnerable populations that experience chronic high levels of stress also known as allostasis load (Rodriquez et al., 2018). These populations experience high levels of obesity and comorbidities (Charmandari et al., 2005; Rodriquez et al., 2018; van der Valk et al., 2018). The bi-directional relationship between obesity and stress has been well documented and continues to be investigated with assessing heterogeneity among various covariates (Cedillo et al., 2019).

Many health conditions and medications can also cause obesity (Balentine, 2015; CDC, 2012). The body and its processes work together to keep the body in the state of homeostasis but because of known and unknown factors, conditions/diseases appear. There are some conditions/diseases that can impact not only how quickly the body metabolizes energy but also the hormone/receptors that signals being full (Herranz, 2003). Most conditions that cause obesity are from an imbalance, hypoproduction, or hyperproduction of a chemical messenger (Ratini,2020). Some conditions include hypothyroidism, polycystic ovaries syndrome (PCOS), depression, and diabetes (Ratini, 2020). Another closely associated influence on obesity are medications (CDC,2012). Through many different pathways, medications such as corticosteroids and antiretroviral art therapy (ART) affects metabolism, the way the body uses energy; coupled with the other overlapping causes and risk factors these can increase the susceptibility and severity of childhood obesity (Balentine, 2015; CDC, 2012; Verhaegen & Van Gaal, 2019).

A final cause of obesity is sleep patterns (Balentine, 2015; CDC, 2012). There are metabolic processes that happen during different stages of the sleep cycle (Bonanno et al.,2019). Sleep is important for energy metabolism, but there has been a relationship investigating quality of sleep-in metabolic processes (Anam et al., 2022). Anam et al. (2022) reported that when compared to those who got 8 or more hours of sleep, there was a statistically significant 73% (OR = 1.73, 95%CI = 1.21-2.47) increase of odds of being obese or overweight amongst those who received less than 8 hours of sleep. Although the complete pathway is not fully understood, several studies have reported that when compared to children (5–9 years old) who get 10 hours or more of sleep, children who do not get 10 hours of sleep a night have a 1.5–2 times risk increase of obesity (Anam et al., 2022; Jiang et al., 2009; Padez et al., 2009).

Epidemiology of Pediatric Obesity

Childhood obesity is considered a multifactorial epidemic that has become a public health concern (Reis et al., 2020). Childhood obesity is a global issue that was once believed to be a developed country condition is now being observed in middle and lower-income countries (WHO, n.d.). In assessing global trends from 1975-2016, Oceania had the highest average BMI in both boys and girls (BMI: boys=20.059, girls=20.692), followed by European Union (EU) and North America in boys (BMI=19.232) and Latin America in girls (BMI=19.307) [WHO, n.d.; Worldmapper, 2020;]. Many disparities in obesity can be seen on a global and continental scale (González-Alvarez et al., 2020). This section describes the epidemiological constructs of childhood obesity defining the current childhood obesity epidemic.

Prevalence

Childhood obesity is observed globally, from lesser developed countries to developed countries (Callahan, 2019). In 2016, it was reported that the global prevalence rate for childhood obesity was 18% (WHO, n.d.). The only country that outranks the United States in childhood obesity is China with more than 28 million children (age 6-17 years), approximately 29.4% (GBD 2015 Obesity Collaborators,2017; Worldmapper, 2020; Zhang, 2022). From 2017- 2020, the prevalence of childhood obesity in the United States was approximately 19.7% (CDC, 2022). During 2018-2020, including the COVID-19 pandemic, not only did the obesity prevalence rate increase to 22.4%, but the rate of body mass index doubled (CDC, 2022). Obesity is a multifaceted disease/condition where significant differences can be seen across demographics such as race/ethnicity, age groups, geography, gender/sex, and socioeconomic status (Isong et al., 2018).

Socioeconomically, the greatest obesity prevalence rate was seen in the lowest income group (CDC, 2022). Current research does show that there may be a paradoxical relationship between socioeconomic status and obesity, as the prevalence of obesity in the homeless community (both adults and children) is increasing (Koh et al., 2012; Levine et al., 2016). From 2017-2020, the highest prevalence rate of childhood obesity in the US is observed in Hispanic children (28.7%), followed by 24.8% among Black/African American, Non-Hispanic children (24.8%) [CDC, 2022; The State of Childhood Obesity, n.d.]. The lowest obesity prevalence rate, 9.0% was among Asian, Non-Hispanic children (CDC, 2022; The State of Childhood Obesity, n.d.). According to the State of Childhood Obesity in 2021, the six states with higher obesity rates in ages 10-17 than the national rate are all located in the south-Kentucky (23.8%), Mississippi (22.3%), Louisiana (22.2%), West Virginia (21.9%), Alabama (21.8%), and Tennessee (20.8%) [The State of Childhood Obesity, 2021].

Using the 2020 Census data, the child population (0-18 years) was approximately 156, 970 (U.S Census Bureau, n.d.). It has been reported that 1 in 3 children are either overweight or obese (Baltimore City Health Department, 2016). Similar to the continental prevalence rate, in Baltimore obesity tends to impact low socio-economic status and Black/African American population (Loh et al., 2018). For example, in Baltimore, low-income children have a 3.4 increased risk of obesity when compared to affluent children (Hager et al., 2017).

Incidence

In 2016, the US obesity incidence rate was 11.6% (Cheung et al. 2016). The Early Childhood Longitudinal Studies concluded not only were there significant racial/ethnic differences in the incidence of childhood obesity but the greatest cumulative incidence in their nationally representative sample occurred between ages 5-14 (Cunningham et al., 2022). In this longitudinal study they followed kindergarteners until the 5th grade and discovered that in their 2010 cohort, 16.2% of their population were newly considered obese (Cunningham et al., 2022). Additionally, they found that in their 2010 cohort, 16.2% of their population were newly considered obese (Cunningham et al., 2022). Similar high incidence rates for childhood obesity were found in a longitudinal study in Arkansas where 4.8% of their child population became obese between kindergarten and 9th grade (Rouse et al., 2019). Additionally, they reported than those who were obese in kindergarten had a 17.5% increase in odds to be obese in the 8th grade (Rouse et al., 2019). Lastly, they noted a significant interaction between race, sex, time, and childhood obesity (Rouse et al., 2019).

Utilizing a national sample but taking into consideration socioeconomic status, Pan et al. followed over a million Americans that identified as low SES, measured by those who qualified and used Women's, Infant and Children (WIC), a supplemental program that assist women and infants (0-5 years) of low-socioeconomic status have access to healthy foods (Food and Nutrition Services, n.d; Pan et al., 2013). In their nationally representative sample, between 2008-2010, after being followed for 24-35 months, that 11.1% had become obese using the CDC's BMIs for age percentile parameters (Pan et al., 2013). They additionally found higher associations amongst boys of lower SES status as well as an increased risk among Hispanics (35%), and American Indians/Alaskan Natives (49%) when compared to their white counterparts but uncommonly lower among Blacks/ African Americans, Non-Hispanic (8%) [Pan et al., 2013). Majority of the literature reinforces that childhood obesity is not solely a behavioral health condition but influenced through many pathways including but not limited to environmental, structural, economic, social, mental, and genetic (Lee et al., 2019).

Etiology of Type 2 Diabetes Mellitus

T2DM is a metabolic disorder caused by insulin insensitivity, resistance, or combination of both resulting in hyperglycemia (Gerst et al., 2019). These insulin abnormalities derive from the body's inability to detect insulin clearance (IC), the process where the organ or cell regulates insulin availability, concentration, and use (Lee et al., 2013). It is well documented that people with T2DM have lower insulin clearance rate (ICR) [Koh et al., 2022]. The literature regarding predictors or determinants of IC/ICR are inconclusive but primarily assessed cross-sectionally. The most cross-sectional consistent determinant/predictor of IC/ICR has been physical activity, primarily in mice, adult men (healthy and insulin dependent) but not children (Kurauti et al., 2016; Tuominen et. al, 2008). However, using the Prospective Metabolism and Islet Cell Evaluation (PROMISE) cohort not only was physical activity found not to be significant but race/ethnicity, increase in waistline circumference and metabolic disorders were associated with declines in IC/ICR (Semnani-Azad, 2019). Similar racial/ethnic differences were found between Black/African American men and White European men (Lawda et al., 2022).

Because there is biological plausibility and a well-supported dose response relationship between physical activity and insulin clearance, the opposition between the aforementioned study and the majority of the literature is caused by how Semnani-Azad measured physical activity. Using the modified activity questionnaire (MAQ) confines physical activity to an exact list of recreational activities whereas the other studies used Metabolic Equivalent of task (MET), which measures intensity (Jetté & Blüchmen, 1990). With the increase prevalence and incidence of childhood obesity, researchers have begun investigating the role that age and puberty may have on IC/ICR. When compared to pre-pubescents, adolescents in both sexes, and of all weight status had increased in insulin resistance (Jeffrey et al., 2012; Kelsey & Zeitler, 2016).

While it is unclear when in puberty IR begins there have been few longitudinal studies to explore this relationship. In a longitudinal study, Jeffery et al., aim to evaluate the relationship between IR, insulin-like growth factor 1 (IGF-1) with age, sex, and obesity (measured through adiposity). Jeffery et al., observed IR began around the age of 7 and 3-4 years after sexual maturation classified in girls by producing luteinizing hormone (LH) and in boys by rating where they ranked on the Tanner stage (TS)[(Jeffery et al., 2012]. It was also adduced that similar to the literature, girls had higher IR and that the difference in 34% variance of IR amongst boys and 35% in girls were explained by increasing weight and IGF-1 combined (Jeffrey et al., 2012; Kelsey & Zeitler, 2016).

Epidemiology of Pediatric Type II Diabetes Mellitus

Prevalence

According to the Centers for Disease Control and Prevention (CDC), while 37 million Americans are diagnosed with diabetes mellitus, 90-95% of those cases have Type 2 (CDC,2021). T2DM was once considered to be an adult's disease as it was usually seen in primarily adults aged 45 and older but it is becoming more prevalent in youth and young adults (CDC,2021). From 2001 to 2017, the prevalence of type 2 diabetes in youth were 0.34% (2001), 0.46% (2009), 0.67% (2017), respectively (Lawrence et al., 2021). In this study analyzing the SEARCH for Diabetes in Youth Study, Lawrence et al., 2021 reported that from 2001-2017, there has been a 95.3% relative increase in overall T2DM prevalence amongst youth (Lawrence et al., 2021). In the United States, there are approximately 283,000 American youths to have T2DM (American Diabetes Association, n.d.). Similar to other conditions, the prevalence of T2DM significantly differs by sex, race/ethnicity, and socioeconomic status where the more prevalent cases of this chronic condition are more observed in minorities (Jensen & Dabelea, 2018; Lawrence et al., 2021).

Incidence

Since the significant increase in body mass index (BMI) and sedentary lifestyle amongst youth and young adults have caused concerned that there may be an increase in T2DM (Lawrence et al.,2021; Sanyaolu et al.,2019). Between 2002 and 2015 the incidence of T2DM among youth and young adult increased by 4.8% each year; with significant differences in racial/ethnic groups (Divers et al., 2020).

Although 34.5% of US adults are pre-diabetic, 18% of adolescents are pre-diabetic and 24% of young adults are pre-diabetic (Andes et al., 2021; US Preventive Services Task Force, 2021). Aiming to reduce and eliminate the increasing cases of T2DM amongst youth and young adults most of the literature conducts prospective research. Utilizing the National Growth and Health Study for baseline and the Princeton Follow-up Study for diabetic, Morrison et al. concluded that black race, childhood glucose level of 100 mg/dL or higher, and high levels of high-density lipoprotein (HDL) were predictors of T2DM later in life (Morrison et al., 2010). Whereas Morrison et al., study sample consisted of only girls, Franks et al., conducted a longitudinal study consisting of nondiabetic American Indians (Frank et al., 2007). Similar to Morrison et al., Frank et al. reported that lower levels of HDL and regulated glucose homeostasis were protective factors in decreasing risk of T2DM with other stronger predictors being waist circumference, and BMI (Frank et al., 2007).

Environmental Role on Health Outcomes

Environment plays a vital role on health and wellbeing (CDC,2018). Environment is considered in the SDOH under the domain of neighborhood built and environment and has been posited to influence 10% of health outcomes (Magnan, 2017). Environmental factors of shared spaces are significant explanations for the vast differences in health status across many geographic areas (Alpert, 2018; Woolf &Aron, 2013). Jian et al., discovered that environments with higher environmental quality index (EQI) scores, representing neighborhood disadvantages was associated with a 3.22% increased risk in mortality (Jian et al., 2017). Outcomes influenced by environmental determinants of health (EDHs) has been observed from spatial patterns since John Snow during the well-known cholera occurrence to a most recent example of the Flint water crises or COVID-19. Air quality, water quality, housing conditions (lead paint), walkability, infrastructure, botanical sexism, greenspace availability and food insecurity are just some examples of EDHs.

Whereas EQI focuses on environmental factors, area deprivation index (ADI) emphasizes socioeconomic constructs. Not only was increased risk for mortality and a host of health outcomes found using the ADI, but it was also reported that when compared to those who live in a less disadvantaged neighborhood there was a 70% increase of odds to be readmitted to a hospital (Hu et al., 2018).These spatial patterns can be influenced by socioeconomic position and race/ethnicity, but it is well documented that health differences persist after controlling for socioeconomic status, race and ethnicity (Woolf & Aron, 2013) . Pertaining to multimorbidity, when controlling for age, sex, race, and ethnicity, and compared to those with lower ADI scores, there was a 78% increased risk of multimorbidity and 92% increased risk of severe multimorbidity in those with higher ADI scores, signifying higher neighborhood socioeconomic disadvantages (Chamberlain et al., 2020).

Environmental Role on Childhood Obesity

Food environment is often measured by food availability, affordability, accessibility, and acceptability (Sawyer et al., 2021). Many studies investigating the role that environment has on childhood obesity evaluates the potential relationship cross-sectionally. In a cross-sectional study, observing children in grades 1-5 in Montclair, California and utilizing questions from the National Children Health Survey (NCHS), Reis et al aimed to describe the contribution that parent's SES, food environment and built environment on childhood obesity. They measured food environment by the presence of grocery stores and fast-food restaurants; and built environment by perceived safety and presence of parks and recreation centers in the area (Reis et al., 2020). Although there was no association between higher BMI and food environment, they found associations between higher BMIs and neighborhoods perceived to be less safe and with less parks and recreation centers (Reis et al., 2020). Similar findings utilizing the Early Childhood Longitudinal Study-Kindergarten Class (ECLS-K) reported no associations between BMI and food outlet per population, food environment indices or type of food (Shier et al.,2012).

Although the nexus between food environment and obesity may be inconclusive there is literature that reports an association. In evaluating the relationship between obesity amongst public school students in New York City and food environment, Elbel et al. reported that there was a 2.2% to 4.5% decrease in obesity amongst those that lived further than 0.025 miles from the nearest fast-food restaurant (Elbel et al., 2020). Instead of measuring food environment as distance from school to the nearest fast-food restaurant, Fietchtner et al. found that when compared to children living further away from a fast-food restaurant or full-service resident, children living closer had a higher BMI *z*-score of 0.09 and 0.07 units (Fiechtner et al., 2015). In a national representative sample, the Early Childhood Longitudinal Study- Kindergarten (ECLS-K) reported that in 2007, there was 1.27 (95% CI=1.02-5.19) higher risk in obesity amongst school children living near fast-food restaurants as well as gender differences; with girls having 1.41 (95% CI=1.09-8.12) increase of risk of obesity when living near a convenience store (Jia et al., 2019).

Furtherly, to help combat food insecurity, the U.S government implemented the Supplemental Nutrition Assistance Program (SNAP), a program to help make food accessible for low-SES citizens. There are limited restrictions on the type of food a SNAP recipient can purchase. Gorski et al. analyzed the National Household Food Acquisition and Purchase Survey and identified that not only was there 1.10 (95% CI=1.03-1.17) increase in odds of obesity amongst children with greater access to grocery stores overall, but 1.14 (95% CI=1.05-1.24) increase in odds of overweight/obesity among SNAP qualified children with greater access to grocery stores overall (Gorski et al., 2018). Even though there are limited studies evaluating the relationship between food affordability and childhood obesity, there have been studies looking at the policy changes for food programs as well as the change of prices for different foods. For example, before the 2009 change of WIC approved food products, childhood obesity in 2-4 years old was annually increasing by 0.23% points but after the change that reflected dietary guidelines there was an annual 0.34% decrease points in prevalence (Daepp et al., 2019).

In 2011, The United States Department of Agriculture (USDA) analyzed price databases and the ECLS-K to investigate the impact that price can have on a child's weight. They reported that raising the cost of foods high in sugar, salt and fat but lowering the cost for cruciferous vegetables and low-fat milk were associated with lower BMIs in children (USDA, 2011). Aforementioned that diet and sedentary lifestyle are the most common contributors to obesity. Utilizing the 2007 NCHS in which they expounded on variables of interest such as sidewalks/walking paths, access to library or bookmobile, access to parks or playgrounds, vandalism, presence of litter and neighborhood safety; they discovered that neighborhoods with unfavorable social conditions had higher odds of children with obesity and overweightness, approximately 20-60% higher odds than children living in favorable conditions (Singh et al.2010). In aims to explore and compare large geographical areas, Nguyen et al. collected 430,000 images of Salt Lake City, Chicago, and Charleston to measure neighborhood-built environment (defined by street greenness, crosswalks, and tall buildings) influence on BMI. They deduced that cities with higher percentages of street greenness, crosswalks and tall buildings had 25%-28% lower prevalence (Nguyen et al., 2018).

Walkability is often used as a measure of physical activity. Stowe et al. analyzed the Walkscore from almost 13,500 southeastern third to fifth graders by using their home address to evaluate its relationship with obesity. Walkscore encompasses intersection density, block length and amenity density (food deserts/food swamps, parks/greenspace, and recreation centers). Stowe et al. reported an inverse relationship between walkscore and BMI as well as differences in walkscore amongst rural and urban students (Stowe et al., 2019). Outside of those being home-schooled, some children spend great amounts of time at school where they are allotted time to exert energy during recess. The CDC recommends that children have at least 60 minutes a day for physical activity (CDC,2022). Analyzing the 2013-2017 NHANES, when compared to children who participated in recess 5 times a week for more than 30 minutes, there was a 1.06 (95% CI=0.44-2.53) increase in odds among males and 1.80 (95% CI=1.03-3.15) in females of overweightness or obesity (Rogers et al., 2022).

While majority of studies are cross sectional, the Early Childhood Longitudinal Study- Kindergarten (ECLS-K) cohort followed kindergarteners until 8th grade (Jia et al., 2019). The exposure variables of interest were street intersection density (implying walkability), residential density (implying street life and physical activity), recreational facility density (physical activity opportunities), and fitness facility density (physical activity opportunities). [Jia et al., 2019]. After 9 years, children who lived in areas with higher residential density, intersection density and both physical and fitness facility densities had lower child BMIs (Jia et al., 2019). Mirroring the results of this study but using the Mothers and Their Children's Health (MATCH) study, Mcalister et al. explored the cross-sectional and longitudinal associations between BMI and physical activity outside of school. Categorizing physical activity into three-levels: sedentary lifestyle, light physical activity and moderate to vigorous physical activity, and measuring obesity and overweightness by body fat percentage, Mcalister reported inverse associations between physical activity and body fat percentages both longitudinally and cross-sectionally in only boys (Mcalister et al., 2021).

Environmental Role on Type 2 Diabetes Mellitus

Similar to obesity, the environment has an impact on the severity and susceptibility of T2DM (Yu & Robinette, 2021). Some of the well documented environmental factors include stress, lack of physical activity, and polluted natural determinants (air, soil, water) [Raman, 2016]. Many longitudinal studies have reported that an increase in physical activity is associated with a 20-30% reduction in type 2 diabetes risk (Gill & Cooper, 2008). There is limited evidence evaluating the relationship between type 2 diabetes and physical activity in U.S children. Although there is limited evidence, there are studies observing adolescent relationship through the proxy of watching tv, implying a sedentary lifestyle (Schmid et al., 2021). In a longitudinal study, there was 1.34 (95%=1.05-1.70) increase in risk for T2DM among those who watched more than 3 hours of tv a day as young adults (Schmid et al., 2021). This association was only seen amongst women. A similar proxy variable to represent a sedentary environment was used amongst young adults and adolescents from the National Health and Nutrition Examination Survey (NHANES) to investigate the relationship between tv time, computer game time and blood glucose control (Jashinsky et al.,2016). They discovered that for every one unit increase in computer game time there was a positive correlation in blood glucose control (Jashinsky et al.,2016).

Similar to obesity, there is not much evidence researching the relationship between environmental role on pediatric T2DM. In studies observing adults, food environments were found to be inconclusive in increasing the risk of T2DM (den Braver et al., 2018). The heterogeneity of the samples may be the cause, but majority studies have alluded that proximity may not convey accessibility especially since people may prefer quantity over price (Dendup et al., 2018). In addition to the food environment, built environment has more conclusive results. In both an ecological and cross-sectional study higher walkability scores were associated with lower risk of T2DM (Dendup et al., 2018; Lee et al., 2015).

Mirroring the results, Nguyen et al. reported that compared to individuals living in zip codes with less green streets, cross walks, and tall buildings, those living with more green streets, cross walks, and tall buildings there was a 12%-18% lower prevalence of T2DM (Nguyen et al., 2018). Pulling Kuhn incorporated geographic information systems (GIS) to measure the availability of areas that could be used for physical activity (parks, recreation centers, gyms etc.) and a established a new variable that assisted in the conclusion that in Baltimore areas with high physical activity location availability scores and the presences of recreation centers had longer and more intense physical activity (Pulling Kuhn et al., 2021).

Epidemiological studies suggest a strong association between types of food and T2DM in youth and adolescents, specifically sugar-sweetened beverages (Yoshida et al., 2018). Appeared to children who were not regular consumers of sugar-sweetened beverages between meals, children who were regular consumers had 2.4 (95% CI=1.473-3.946) greater odd of being overweight (Dubois et al.,2007). In a longitudinal study, following middle school students over two years discovered that for every additional sugar beverage, there was a 1.60 (95% CI= 1.14-2.24) increase in risk of obesity (Ludwig et al., 2001). In a retrospective cohort study, Abbasi et al. declared that compared to a counterpart with a normal BMI, children with obesity had a quadrupled risk of being diagnosed with T2DM by the age of 25 (Abbasi et al., 2017). Larson et al. performed a literature review between 1985 and April 2008, and discovered that low SES communities, rural communities and communities often are classified as food deserts but food swamps that impact their food behaviors and choices (Larson et al., 2009). Many local studies such as Madsen et al. found that sugary beverages were mostly purchased in convenience and corner stores and because they were so ubiquitous in urban and low-income areas, purchase patterns should be prioritized (Madsen et al., 2019).

Redlining

Redlining was a discriminatory policy/practice that alerted mortgage lenders of risky applicants based on their race/ethnicity (Shaker et al., 2022). Aforementioned, the practice of redlining resulted in zones assigned color coded grades. Grade A was color coded green and represented good status, B was assigned the color blue and symbolized still desirable, Grade C was color coded yellow and characterized definitely denying and Grade D assigned the color of red and represented hazardous environments (Winling & Michney, 2021). Although redlining has been made illegal with the Fair Housing Act of 1968 (FHAct) it still occurs covertly (Columbia Broadcasting Services, 2020). In 2018, Jan published that in Baltimore, race/ethnicity played a more significant part in lending practices than income (Jan, 2018). Additionally, there are transgenerational implications of redlining that still persist in many US cities today (Columbia Broadcasting Services, 2020). Furthermore, past HOLC grades and segregation explain 25 % in variation in income poverty and 23% of economic inequality (Andres et al.,2022).

Best and Mejia investigated the state of redlining/residential segregation in 138 cities across the U.S and found that majority of the cities that were redlined in the early twentieth century were still being impacted with more U.S cites in the South being impacted relative to the North (Best &Mejia, 2022). Redlining was more than structurally restricting non-native, non-white applicants to “hazardous areas”, those living in these areas were charged higher interest rates for lower property value homes than compared to “best” areas which led to many foreclosures and poverty (Mendez-Carbajo, 2021). With the increase of poverty, came the increase in crime, and drug use, which led to many abandoning their homes for better schools and opportunities (Caine,2022). When compared to areas not classified as “hazardous”, areas that were considered “hazardous” had 10% higher levels of housing vacancy and lots (Meier &Mitchell, 2022). Sociologist have coined the term concentrated disadvantage. Concentrated disadvantage is defined as “the phenomenon of spatial clustering of economically or socially disadvantaged individuals within a set of neighborhoods and the resulting feedback effects that exacerbate the problems of poverty” (Jargowsky & Tursi, 2015). A study reported that redlining is a significant indicator of neighborhood disorganization, concentrated disadvantage, and crime (Powell &Porter, 2022). In redlined areas in Los Angeles, CA, Anders discovered that 50% increase in crime was associated with areas historically categorized as “hazardous” (Anders, 2019). Another study looking at national data, reported that when compared to non-redlined areas, redlined areas had a 60-70% increase in crimes, specifically homicide (Powell & Porter, 2022).

The collection of these “hazardous” regions influenced the derogatory term, “ghettos” to represent areas starved of social capital where minorities were often forced to lived (Bouie, 2017). There have been many studies investigating the connection between SES and environmental health with many psychological studies conveying that those in poorer communities are more likely to litter because of lack of infrastructure and investments (Schultz et al., 2013). After having areas in Philadelphia gentrified, the new residents observed the amounts of litter and trash that plagued their new community. Utilizing the Litter index, they were able to not only recognize that areas with higher litter indexes were observed in lower SES areas but that when overlapped with the 1930’s HOLC map, areas with higher litter indexes were areas classified as “C” and “D” (Marie Porter,2020). Similar results were seen in an ethnographic study investigating how litter serves as both a physical and social disorder. Over three years of interviewing and observing Penn Hill residents, Murphy translated that the residents (black and white) associated littering with poor black renters or public spaces that they dominantly may use (Murphy,2012).

Redlining Impact on Health Outcomes

The transgenerational implication of redlining is well documented (Aaronson et al., 2022). Not investing in risky environments is shown not only in social mobility but infrastructurally (Aaronson et al., 2020,2022). According to Smith et al., there is a clear distinction between neighborhoods that were historically considered best and those considered hazardous because of redlining (Smith et al,2019). The differences include those “hazardous” neighborhoods often occupied by Black, Indigenous, People of Color (BIPOC) having factors that do not promote a healthy lifestyle but a variety of chronic disease risk factors (Bower et al., 2015; Huang & Sehgal, 2022; Richardson et al; 2020; Smith et al., 2019). Robust literature has often reported an association of decrease walkability, increase of food deserts, increase in food swamps, lower birth rates, higher tobacco retail densities, lack of playgrounds and recreation centers, federally qualified health centers (FQHCs), and areas historically redlined (Howell &Booth, 2022; Nardone et al.,2020; Schwartz et al.,2021).

For example, in an ecological study in California, Nardone et al. discovered that when compared to areas historically categorized with the Grade of D not only had higher diesel exhaust emissions but 2.4 times higher in emergency department admissions for asthma (Nardone et al., 2020). Similar findings were found amongst low-birth-weight outcomes in California, Nardone et al. discovered that the odds of low birthweight worsened with the higher the grade. Specifically, there was a 1.02 (95% CI=1.00-1.05) increase in odds of a low birth weight amongst women living in areas historically given Grade of C when compared to women living in Grade B areas (Nardone et. 2021). Examining behavioral influences such as smoking in 13 cities in Ohio, Schwartz discovered that as HOLC grade worsened there was an increase in tobacco retail density (Schwartz et al., 2021). This finding is supported by the literature that while these areas may be food deserts they have high density in convenience stores, tobacco marketing and alcohol outlets (Kong et al., 2022; Trangenstein et al., 2020). Furtherly amongst COVID-

19 cases, when compared to neighborhoods/communities that were assigned the grade of A, those who resided in areas assigned the grade of D have a life expectancy lower by 3.6 years (Richardson et al., 2020).

Huang & Sehgal acknowledged the current health status of Baltimoreans and aimed to investigate if the implications of redlining influenced that current state. Utilizing the Baltimore's Neighborhood Indicators Alliance (BNIA) for health outcomes such as life expectancy, birth outcomes, teen pregnancy, and lead exposure they overlayed the redlining map from the Mapping Inequality Project based by the HOLC map. They discovered that individuals who live in a historically categorized hazardous areas have a life expectancy lower than 4.01 years whereas those who lived in definitely denying areas had a 5.36-year reduction in life expectancy (Huang & Sehgal, 2022). After controlling for SES and percentage of Blacks/African Americans not only did the reduction remained statistically significant but increased to 5.23 reduction in hazardous areas but decreased to 4.93 years in the definitely denying category (Huang & Sehgal, 2022).

Redlining on Childhood Obesity

The result of redlining is disinvestments (Aaronson et al., 2020; Kendi, 2017). Disinvestment is the removal of capital or financial interest to improve a shared space (Aaronson et al., 2020). This circumstance coupled with obesogenic risk factors, and other social conditions not only characterize the high prevalence, and incidence pediatric obese rates but the perpetuation of racial disparities (Goodman et al.,2018; Mackey et al., 2022). Aforementioned, the two most common causes of obesity are diet and a sedentary lifestyle.

Spatial analysis has helped with the mapping of food insecurity, which captures food deserts and food swamps and how they disproportionally plague urban, predominantly minority and low SES communities (Zhang &Debarchana,2016). In 2020, 10.5% of U.S. households were classified as food insecure (United States Department of Agriculture, n.d.). When compared to children in food-secure homes, children in food-insecure households had 5 times higher odds of being obese (Kral et al.,2017).

Food insecurity is not only about how often one eats, but what an individual may eat (Shaker et al., 2022). Blacks/African Americans and Hispanic children are not only more likely to reside in areas swamped with fast foods (food swamps) but are more likely to be exposed to less nutritionally dense foods (Byrd et al,2018). Supermarket redlining, or the discouragement for major supermarkets to be located in risky neighborhoods have been associated with obesity in many cities (Shaker et al., 2022). In Indianapolis and utilizing census data, federal poverty levels and the HOLC map, Andres et al. discovered that redlining explained 38% SNAP users and 51% in differences amongst neighborhoods (Andres et al.,2022). Powell et al. aimed to look at the impact of redlining on food access in US urban cities. Similar to Andres and the majority of the literature they used the HOLC map to observe the zoning grades, the American Community survey for demographics and for food access they used the most recent measure of food deserts, the USDA's Food Access Atlas. Creating three logistics models and controlling for income, Powell et al. reported that by zip codes, supermarkets were 52% (*t*-statistic=-9.62, *p-value*=<0.01) less available in predominantly Black and 32% (*t*-statistic=-8.44, *p-value=<0.01)* Hispanic communities (Shaker et al., 2022).

Although there is robust evidence of a relationship between historically redlined areas and food insecurity, a study in Baltimore assessed if redlining, gentrification, or blockbusting were associated with food environment (Sadler et al.,2021). Sadler et al. found that blockbusting was more associated with poor food access and that areas historically redlined had better healthy food availability index (HFAI) scores (Sadler et al.,2021. The other common cause of obesity is living a sedentary lifestyle. Redlining has impacted infrastructures that could promote a physically active lifestyle (Huang & Sehgal,2022). Utilizing HOLC data, the 1940's Census and 2010 greenspace (parks, community gardens) data, there was an association between neighborhoods with worst HOLC grades and paucity of present-day greenspace (Nardone et al., 2021). Walkability was found to not only be a predictor of lower BMI but was associated with a 10% decrease in obesity prevalence (Rundle et al.,2009). Like similar cities, redlining has influenced an obesogenic environment in Baltimore (Boone et al.,2009). In 2009, it was reported that underserved areas had a greater walkability to parks but less acreages in their parks (Boone et al.2009).

Redlining on Type 2 Diabetes Mellitus

Similar to common causes of obesity, physical activity and diet are common in the diagnosis and prognosis of T2DM (Pearson, 2019). As mentioned earlier, there is generally a relationship between areas impacted by redlining and food environment, where residents either don't have access to affordable fresh nutritional foods or reside in an area plagued with fast food, convenient stores, liquor stores or tobacco retailers (Schwartz et al., 2021; Shaker et al., 2022). Additionally, areas historically categorized as risky investments tend to be associated worst diabetic related affects (Ogunwole & Golden, 2021). In Seattle, Washington, Linda et al., used the HOLC map, morality and years of lost life (YLL) were used to measure the implications of redlining on present day diabetes mortality. With spatial regression analysis, Linda et al. reported that between the years of 1990 and 2004, redlining explained 45%-65% diabetes mortality rate (Linda et al., 2022). In the same analysis, they discovered that in 2014 for every increase in HOLC grade with 53.7% increase in mortality and almost 67% higher diabetes YLL (Linda et al., 2022).

LaVeist recognized the implications that redlining/residential segregation has on health outcomes and conducted an observational study to evaluate if the racial and ethnic disparities conveyed by the prevalence of diabetes would still exist if Blacks/African Americans and Whites lived under the same conditions (LaVeist et al., 2011). Deciding to use samples from communities with 35% Blacks/African Americans and Whites, Laviest used Southwest Baltimore. Using questions from NHIS, NHANES and Medical Expenditure Panel Survey (MEPS) to create the Exploring Health Disparities in Integrated Communities-Southwest Baltimore (EHDIC-SWB) and compare it to the results of each nationally representative survey/sample. While the NHIS reported that Blacks/African Americans had a 1.61 (95% CI=1.26-2.04) increase of odds in T2DM when compared to whites, the EHDIC-SWB concluded that the prevalence was similar amongst Black/African Americans and whites in Southwest Baltimore, 10.4 and 10.5%, respectively (LaVeist et al., 2011).

To support the literature assessing the relationship between T2DM and redlining, Ogunwole and Golden proposed a conceptual model that describes the root of diabetes as racism (Ogunwole & Golden, 2021). They posited that racism created residential segregation and through disinvestments of these community poorer educational systems, creation of ghettos (overcrowding, poor housing), increase in environment toxin and infectious exposures with chronic inflammation (Ogunwole & Golden, 2021). All these conditions increase susceptibility and severity of diabetes (Ogunwole & Golden, 2021). Those aforementioned conditions have an ambi-directional relationship with low literacy rates, lower SES (education and employment) and poor nutrition which are often associated with risk factors for T2DM as well as associated comorbidities (Ogunwole & Golden, 2021).

Like obesity, not only is T2DM multifactorial but disparities are present (Bingham, 2022). Although the relationship between neighborhood and built environment, obesity and diabetes is not fully understood, there are numerous studies inquiring on many levels. Significant predictors of T2DM only household poverty, status, gender, and family history (Gaskin et al., 2014). In exploring the nexus of race, SES, and place amongst the disparities in diabetes, it was reported that not only did living in a poor area increase the odd of T2DM in Blacks and poor whites, but when compared to whites, blacks had higher odds of T2DM (Gaskin et al., 2014). Ludwig et al. reported that moving from a neighborhood with high poverty to a neighborhood with lower poverty has a positive association with reduced obesity and T2DM (Ludwig et al. ,2011). In perceived disorderly neighborhoods (neighborhoods with vacant houses, vandalism, trashy) there were higher rates of T2DM risk (Yu et al., 2021).

Summary

The purpose of this quantitative study was to determine if the presence of neighborhood detraction elements as an impact of redlining was associated with T2DM and obesogenic risk amongst the pediatric population. The previous research discussed in this chapter have provided an extensive background information, biological plausibility/ pathogenesis, and it has established a linkage between policy, health outcomes and location utilizing similar variables of interest. Although this literature review conveyed the aforementioned, there is limited to no evidence evaluating these relationships as it may pertain to youth and young adults. Therefore, future research was needed. This study enhanced research on the transgenerational implications of redlining on pediatric health outcomes. Chapter 3 identifies the research questions for this study as well as distinguishes the methods that were used to address this gap in the literature.

Chapter 3: Research Methods

The purpose of this quantitative research study was to determine predictors of pediatric T2DM and whether the presence of neighborhood detraction elements was associated with obesity on T2DM in the pediatric population. This chapter highlights the methodology that was used in conducting this cross-sectional study. First, I convey the research design and rationale. The remaining sections of this chapter report the sampling procedures, study population, sample size, study instrument, study variables, data access, and data analysis. Lastly, the chapter concludes with a discussion on threats to validity and ethical considerations.

Research Design and Rationale

This study was a quantitative, cross-sectional study design to analyze secondary data from the 2019-2020 National Children's Health Survey (NSCH) including sociodemographic variables (age, race/ethnicity, sex, gender, family structure and SES), environmental variables (food insecurity, accessible playgrounds and parks, accessible safe neighborhoods, safe walking paths and accessible recreational centers and presence of detracting neighborhood elements), physical activity, T2DM, and BMI. The research questions for this study examined the relationship between presence of neighborhood detraction elements, and obesogenic risk factors on T2DM:

- RQ 1: What is the association between obesity and the presence of detracted neighborhood elements in the pediatric population when controlling for age, race/ethnicity, sex, and socioeconomic status?

- RQ 2: What is the association between type 2 diabetes mellitus (T2DM) and the presence of detracted neighborhood elements in the pediatric population when controlling for race/ethnicity, sex/ gender, and socioeconomic status?
- RQ 3: Does demographic (sex, age, race/ethnicity, socioeconomic status, and family structure), environmental (food insecurity, accessible playgrounds and parks, safe neighborhoods, safe walking paths, accessible recreation centers and presence of detracting neighborhood elements), physical activity, and body mass index (BMI) have an influence on the prevalence of type 2 diabetes among the pediatric population?

To understand the potential pathway between environment and obesity on T2DM in the pediatric population, I examined the association between pediatric obesity and presence of neighborhood detraction elements when controlling for age, race/ethnicity, sex, and SES. I also evaluated the association between pediatric T2DM and presence of neighborhood detraction elements when controlling for race/ethnicity, sex, and SES. Finally, I investigated the potential influence of demographic variables, environmental variables, physical activity, and BMI have on U.S. pediatric T2DM prevalence.

Methodology

This quantitative cross-sectional analysis included secondary data collected by the NSCH. To understand the physical, environmental, biological, psychosocial, and economic health of children in the United States, three federal agencies aimed to collect snapshots beginning in 2001 (Ghandoue et al., 2018). Before 2016 not only was the survey conducted via random dialing, but it was not administered annually. As of 2020 the design has been restructured to include more questions focusing on different areas of health, more questions for children with special needs and is now being collected annually and merged to investigate trends (Ghandone et. al, 2018, CAHMI,2022). Similar to the analysis of this project, the NSCH is a cross-sectional dataset that collects health status and SDOH by the provider of the home.

Study Instrument

The NSCH is sponsored and directed by three federal agencies—the U.S Department of Health and Human Services (HHS), Health Resources and Services Administration (HRSA) and the Maternal and Child Health Bureau (MCHB)—but is conducted by the U.S. Census Bureau (CAHMI, 2022). The data from this survey are public with the exclusion of specific identifiers due to confidentiality restrictions. On average, this survey takes about 33 minutes to complete (CAHMI, 2020). This survey includes questions that the parental figure answers pertaining to

> demographics, health and functional status, health insurance coverage, health care access and utilization, medical home, early childhood (0-5 years) issues, issues specific to middle childhood and adolescence (6-17 years), family functioning, parental health status and family, and neighborhood and community characteristics. (CAMI, 2022, p.2).

The goal of this survey is to estimate national and state level prevalence of the overall health status of U.S. children and young people and investigate the social determinants of health that may influence the current status to help create data driven policies (CAMI, 2022).

Study Population

The NSCH sample is composed of non-institutionalized children aged 0-17 years in each state (CAHMI, 2022). The 2019 NSCH was conducted between June 2019 and January 2020. The total number of respondents were 29,433. The 2020 NSHC was conducted from July 2020 to January 2021. The total number of respondents were 42,777. Between the years of 2019 and 2020 there was a total of 72,210 nationwide parents that completed this survey about their non-institutionalized youth and teens between the ages of 0–17.

Sampling Procedures

Using an address-based sample that cover the 50 states and District of Columbia, households are selected with a mutually exclusive multi-stratum approach. The first stratum selects addresses that are “explicitly linked to children” (CAHMI, 2020, p. 2), such as tax documents (IRS 1040 document), Medicare applications/submissions, social security database or tenant rental data). The second level in sampling households with children are addresses that are probably linked with children. For example, tenant data such as those living in government assisted housing. The last strata consisted of the remaining addresses.

Following the selection of the addresses, households receive an invitation to answer a screener questionnaire; once that is submitted and analyzed, the topical NSCH is administered to that same household to be completed for one designated child per household (CAHMI, 2022). The selection of the child in each household is “based on the number of children in the household, the special health care needs status, and age

(CAHMI, 2022, p. 3). Since 2016, the NSCH has changed how their data are collected from random digit dial to offering the survey through the mail or electronically. For households that do not respond, there are two more reminders sent. The 2019 and 2020 NSCH was combined for this analysis with about 1416 surveys being completed per U.S state (CAHMI, 2022).

For analysis purposes in this quantitative cross-sectional study, the inclusion criterion was similar to that of the NSCH—only consisting of 0–17-year-old, non-institutionalized children. The exclusion criterion consisted of children who had incomplete/omitted responses in the survey among the variables of interest. A G*Power analysis was conducted to test if the sample size of the NCHS was sufficient for this study. To conduct the power analysis, a logistic (non-parametric) design using all 14 variables was selected for power based on the known sample size in the NSCH (n = 72,210), proportion of 0.67 (based on the 2017 prevalence of pediatric T2DM), and a two-tailed test with an alpha*(α)* level of 0.05. The G*Power analysis concluded that a sample size of 889 (n = 889) was needed for this study.

Study Variables

Demographic Variables

The following demographic variables were taken from the 2019–2020 NSCH. Demographic variables are variables that describe the distribution of a sample or population (Lee & Schuele, 2010). All variables associated with this dataset are attached to unique household identifiers (HHID), which are exclusive identifier numbers given to each household between 2019–2020 that participated in the survey. In addition, Table 1 describes the original formation of variables, variable types, and categories.

Table 1

Demographic Variable

Variable Name	Variable Label	Variable Type	Frequency Category
Sex of Child (sex_1920)	What is the child's sex?	Categorical (Dichotomous)	1= Male 2= Female 99= Missing
US Children in 3 age groups (age3_1920)	What is this child's age?	Categorical (Ordinal)	1= 0-5 years old 2= 6-11 years old 3= 12-17 years old
Race and Ethnicity Distribution of the Child Population including Asian data (raceASIA_1920)	What is this child's race/ethnicity?	Categorical (Nominal)	1= Hispanic 2= White, non-Hispanic 3= Black, non-Hispanic 4=Asian, non-Hispanic 5= Other/Multi-racial, non-Hispanic 99= Missing to Hispanic or Race or both
Income Level of Child's Household (povlev4_1920)	What is the income level (federal poverty level, FPL) of the household that this child lives in?	Categorical (Ordinal)	1= 0-99% FPL 2=”100-199% FPL 3=200-399% FPL 4= 400%FPL or greater
Family structure of child's household (famstruct5_1920)	What is the family structure that this child lives in?	Categorical (nominal)	1= Two parents, currently married 2=Two parents, not currently married 3=Single parent (mother or father) 4=Grandparent household 5=Other family type 99= Missing

Environmental Variables

The following environmental variables were utilized from the 2019-2020 NSCH. The classification of these variables is based on environment psychology which conveys that environmental variables are factors that characterize an individual's environment and its' influence on their behavior (Gieseking, 2014). Aforementioned, all variables associated with this dataset are attached to HHID. In Table 2 are the variables, variable types, and categories. The only two variables that were manipulated for analysis purposes were food insufficiency and safe neighborhood. Food Insufficiency was dichotomized to food secure and food insecure with respondents that selected "1" and "2" as being food secure and the remaining choices being categorized a food insecure. Similarly, safe neighborhood was dichotomized; resulting in respondents that agreed ("1") and somewhat agree ("2") that their neighborhood was safe as being combined to represent Safe ("1").

Table 2

Environmental Variables

Variable Name	Variable Label	Variable Type	Frequency Category
Food Insufficiency (FoodSit_1920)	Which of these statements best describes your household's ability to afford the food you need during the past 12 months?	Categorical (Ordinal)	1= "We could always afford to eat good nutritious meals" 2= 'We could always afford enough to eat but not always the kinds of food we should eat" 3= "Sometimes we could not afford enough to eat" 4= "Often we could not afford enough to eat" 99= "Missing"
Food Insufficiency (recoded)			1= Food Secure ("We could always afford to eat good nutritious meals"/'We could always afford enough to eat but not always the kinds of food we should eat" 2= Food Insecure ("Sometimes we could not afford enough to eat"/ "Often we could not afford enough to eat"
Safe neighborhood (NbhdSafe_1920)	Does this child live in a safe neighborhood?	Categorical (Ordinal)	1= Definitely Agree 2= Somewhat Agree 3=Somewhat/Definitely Disagree 99= Missing
Safe neighborhood (recoded)			1= Safe (Definitely Agree/Somewhat Agree) 2= Not Safe (Somewhat/Definitely Disagree)
Sidewalks_1920 (K10Q11)	Children who live in neighborhoods with sidewalks or walking paths	Categorical (Dichotomous)	1= Yes 2=No 99= Missing
Park_1920 (K10Q12)	Children who live in neighborhoods with a park or playground	Categorical (Dichotomous)	1=Yes 2=No 99=Missing
RecCenter_1920 (K10Q13)	Children who live in neighborhoods with recreation center, community center, or boys and girls club	Categorical (Dichotomous)	1=Yes 2=No 99=Missing
Presence of detracting neighborhood elements (NbhdDetract_1920)	Does this child live in a neighborhood where there is litter or garbage on the street or sidewalk, poorly kept or rundown housing, or vandalism such as broken windows and graffiti?	Categorical (Ordinal)	0= Neighborhood does not have any detracting elements 1= Neighborhood has 1 detracting element 2=Neighborhood has 2 detracting elements 3=Neighboring has all 3 detracting elements 99= Missing

Physical Activity Variables

The following physical activity variable was taken from the 2019-2020 NSCH. The parameters of this physical activity (PA) are based on recommendations set by the CDC which encourages children to get at least 60 minutes, three times a week of PA (CDC, 2022). Aforementioned, all variables associated with this dataset are attached to HHID. In addition, Table 3 describes the variables, variable types, and categories. The PA variable was manipulated but remained it remained classified as an ordinal variable. The PA variable renamed Exercise was created based on those who believed their children play for more than 60 minutes either everyday (“4”) or 4-6 days (“3”) were recoded to represent Optimal Exercise (“3”). Those respondents that originally selected 1-3 days (“2”) were renamed to be Moderate exercise; and those that originally selected no days of physical activity were renamed as No Exercise.

Table 3

Physical Activity Variables

Variable Name	Variable Label	Variable Type	Frequency Category
Physical Activity PhysAct_1920	Children who are physically active at least 60 minutes	Categorical (Ordinal)	1= 0 days 2=1-3 days 3= 4-6 days 4=Every day 99= Missing 90= Children aged 0-5 years
Exercise (recoded physical activity variable)		Categorical (Ordinal)	1= No Exercise (0 days) 2= Moderate Exercise (1-3 days) 3= Optimal Exercise (4-6 days; Everyday)

BMI Variables

The following BMI variable was collected from the 2019-2020 NSCH. Amongst youth and young adult, BMI is assessed and reported differently because it is age and gender specific (CDC, 2022). Children under the age of 10 years were not included in this measure because like the other variables in this survey, they are reported by parents; and in a 2003 study reported that parents underestimate weight and overestimate height in children less than 10 years old (Akinbami &Ogden, 2009; CAHMI, 2022). Aforementioned, all variables associated with this dataset are connected by HHID. In addition, Table 4 describes the variables, variable types, and categories. The BMI variable was dichotomized to only recognize normal (normal weight and underweight) and Abnormal (overweight and obese).

Table 4

BMI Variables

Variable Name	Variable Label	Variable Type	Frequency Category
Weight status (BMI) in 4 categories, age 10-17 year (BMI4_1920)	What is the weight status of this child based on Body Mass Index (BMI)-for-age, age 10-17 years?	Categorical (Ordinal)	1= Underweight (less than 5th percentile) 2= Normal weight (5th to 84th percentile) 3=Overweight (85th to 94th percentile) 4=Obese (95th percentile or above) 90= Children aged 0-9 years 99= Missing
BMI (Weight status recoded)		Categorical (Dichotomous)	1= Normal (Underweight/Normal weight) 2= Abnormal (overweight/obese)

T2DM Diabetes Variables

The following T2DM variable was taken from the 2019-2020 NSCH. Aforementioned, all variables associated with this dataset are attached by HHID. In addition, Table 5 describes the variables, variable types, and categories. For analysis and interpretation purposes, Diabetes was dichotomized such that those who responded with "Does not have condition" (1) or "Ever told but does not currently have condition" (2) were jointly recognized as "Not having Diabetes" and those who responded that they currently had the condition being labeled as "Has Diabetes".

Table 5

Diabetes Variables

Variable Name	Variable Label	Variable Type	Frequency Category
Diabetes (Diabetes_1920)	Children who currently have diabetes	Categorical (nominal)	1= Does not have condition 2= Ever told, but does not currently have condition 3=currently has condition
Diabetes (Recoded)		Categorical (Dichotomous)	1= Does Not Have Diabetes ("Does not have conditions"/"Ever told, but does not currently have condition" 2= Has Diabetes ("Currently has condition")

Data Access

The NSCH is a public-use dataset. To gain access to this dataset, the researcher is able to choose the year/s of interest and is able to download the dataset by format of choice. To submit a request for use of the data, there are some questions that must be answered, and a disclosure must be agreed to receive the data. Once the request has been approved, the dataset is emailed to the research in the desired format. After receiving approval from Walden University's Institutional Review Board (IRB), I submitted the request for data use.

Data Analysis

All variables in this analysis, were collected by the U.S Department of Health and Human Services (HHS), Health Resources and Services Administration (HRSA) and the Maternal and Child Health Bureau (MCHB) but included in the 2019-2020 NSCH. Cleaning the data was completed by myself and only will exclude those respondents who did not complete the survey. For this study, Statistical Packages for the Social Sciences (SPSS) version 28 was used to perform Chi *Square* (X^2) *Test,* ordinal, and bivariate logistic regression analyses. The *Chi Square Test of Independence* was used for the independence of the variables by presence of detracted neighborhood elements. The bivariate analysis conducted was to examine the 2019-2020 relationships between the presence of neighborhood detraction elements, pediatric obesity prevalence, and pediatric T2DM prevalence. This analysis conveyed the 2019-2020 relationship between pediatric obesity and pediatric T2DM amongst a U.S. nationally representative sample. The ordinal and bivariate logistic regression analyses were conducted to examine the predicted relationships between two or more variables when holding all other potential influencing variables constant. Lastly, a bivariate logistic regression model was conducted to measure the influencers of the prevalence of T2DM. These statistical tests were conducted to answer these following research questions:

- RQ 1: What is the association between obesity and detracted neighborhood elements in the pediatric population when controlling for age, race/ethnicity, sex, and socioeconomic status?

- RQ 2: What is the association between T2DM and detracted neighborhood elements in the pediatric population when controlling for race/ethnicity, sex, and socioeconomic status?
- RQ 3: Do demographic characteristics (sex, age, race/ethnicity, socioeconomic status, and family structure), environmental (food insecurity, accessible playgrounds and parks, safe neighborhoods, safe walking paths, accessible recreation centers and presence of detracting neighborhood elements), physical activity, and BMI have an influence on the prevalence of type 2 diabetes among the pediatric population?

While all three research questions use logistic regressions, RQ1 and RQ2 used ordinal logistic regressions to explain the relationship between obesity, type 2 diabetes, and the presence of neighborhood detraction elements among NCHS respondents in 2019 and 2020. These analyses allowed the study to establish the measure of association while controlling covariates to get a true measure of association, specifically the adjusted odds ratio (aOR). Both of the analyses reported a standardized coefficient (β) which was exponentially calculated as an aOR. To enhance internal validity in answering RQ1, it was important to control for age, race/ethnicity, sex, and socioeconomic status when assessing the relationship between obesity and the presence of neighborhood detraction elements because age, race/ethnicity, sex, and socioeconomic status are risk factors for obesity. Similar to RQ1, the covariates (race/ethnicity, sex, and socioeconomic status) in RQ2 were controlled because they are known risk factors in the susceptibility and severity of T2DM in the pediatric population (CDC,2022).

RQ3 was answered with a binomial logistic regression modeling. This research question aims to investigate the influence that demographic (sex, age, race/ethnicity, socioeconomic status family structure,), environmental (food insecurity, accessible playgrounds and parks, safe neighborhoods, safe walking paths, accessible recreation centers and presence of detracting neighborhood elements), physical activity and body mass index (BMI) has on the prevalence of T2DM. These variables were included in this research question because they mimic the theoretical framework of this analysis, the SDOH. It is hypothesized that the presence of neighborhood detraction elements as a transgenerational implication of redlining has resulted in disinvested and detracted neighborhoods that may promote unhealthy behaviors, thus influencing the increasing prevalence of pediatric obesity and T2DM in the pediatric population.

The first model evaluated the influence that only BMI has on the diabetes variable. The second model consisted of the first model components but with the addition of the demographic variables (sex, age, race/ethnicity, socioeconomic status family structure). To build on the second model, the third model included the variables in model 2, and the environmental variables (food insecurity, accessible playgrounds and parks, safe neighborhoods, safe walking paths, accessible recreation centers and presence of detracting neighborhood elements). The last model included the same variables from model 3 but with the addition of the exercise variable (originally named physical activity). Similar to RQ1 and RQ2, these different models reproduced aORs. For all research questions, there was a 95% Confidence Interval and *p-value* of 0.05 to establish statistical significance.

Revised Research Design

There were some changes in the data analysis plan when actually working with the secondary data that was approved by Walden University's IRB. As mentioned in Chapter 3, a Chi Square Test of Independence was conducted and while that still occurred in this analysis, to quantify the strength of each relationship of each variable with the primary independent variable, presence of detracted neighborhood element, Cramer's V was utilized. Secondly, two of the variables used in this analysis (specifically BMI and PhysAct) only collected data from a subsection of the sample, 6-17 years old and 10-17 years old, respectively. Since one of the primary dependent variables were not collected from those <6 years old, this part of the sample was removed because while they were originally intended to be the referent group, interpretationally there couldn't be a comparison to the other groups with non-existent data. Thirdly, although research question 1 was initially going to be analyzed using an ordinal logistic regression, it failed the assumptions so a multinomial logistic regression was proposed. Unfortunately, because of the way data collection occurred as stated in the second change in research statement, research question one would be analyzed utilizing a binary logistic regression. Lastly, I changed the classification of food security. While the variable remained a dichotomous variable, I considered those "who always have food and health options access" to be labeled as food secure and the remaining levels to be categorized as food insecure.

Threat to Validity

Internal validity involves the evaluation of how a study was designed, conducted, and interpreted so that the conclusions reported reflect the true relationship between variables in a specific population at a specific time (Andrade, 2018). In the earlier stages of this study, confounding was a threat to internal validity. To address this threat, during the literature review, etiologic factors were acknowledged and compared to the used dataset. Furtherly, those variables that were associated with a risk factor was placed in a logistic regression so that they were controlled. Another threat to internal validity to consider in the NSCH is that all the data reported is self-reported which may be vulnerable to recall bias.

On the other hand, external validity is generalizability (ecological or population) or having the ability to be applicable amongst a broader audience (Bhandari, 2022). Although the dataset used in this analysis is a nationally representative sample, in terms of measuring redlining, there was no exact variable included, which resulted in the use of the most readily available data to simulate. While redlining may produce similar results in disinvestments, redlining severity can differ in many cities. To address this limitation, utilizing ARCGIS or US Census Data and merging GEOIDS from a dataset looking at redlining on a city, state level and requesting the confidential data of this survey would give a better estimate of areas historically redlined in the U.S. Amongst the NSCH data, the sample is addressed based. Excluding those that are homeless or live in shelters may underestimate the prevalence of pediatric T2DM and pediatric obesity.

Ethical Considerations

The data for this study was analyzed under the guidelines of Walden University and the Data Resources Center from which the NCHS was obtained. This project entailed a secondary data analysis. The data came deidentified. As per the guidelines of Walden University, only the codebook was accessed and viewed before submitting and defending the proposal. After submitting the request to the Data Resources Center, the data was stored on my computer in an unopened zipped file until after I had obtained both approval of my proposal as well as IRB approval. Walden University's Institutional Review Board 02-07-23-1050534 was conducted and received prior to the data analysis of the study.

Summary

This chapter provided information for the research study that was designed and conducted. This quantitative cross-sectional secondary data analysis aimed to address three research questions investigating the nexus between pediatric T2DM, pediatric obesity and neighborhood detraction serving as a proxy for residing in a historically redlined area. 14 variables were used to answer the three research questions. Those questions were answered with a combination of Chi-Squared statistics, Cramer V's statistics, and bivariate logistic regressions. Chapter 4 included the results of the data analysis plan investigating the relationship between pediatric T2DM, pediatric obesity, and the presence of neighborhood detraction elements. In addition, Chapter 4, consisted of the results investigating the influence of demographic, environmental, physical activity, and BMI on the prevalence of T2DM in a nationally representative sample.

Chapter 4: Results

The purpose of this quantitative secondary data analysis was to establish predictors of pediatric T2DM in a nationally representative sample as well as assess if the presence of neighborhood detraction elements influenced obesity on T2DM. This purpose was assessed by answering the following three research questions:

- RQ 1: What is the association between obesity and detracted neighborhood elements in the pediatric population when controlling for age, race/ethnicity, sex, and socioeconomic status?
- RQ 2: What is the association between type 2 diabetes mellitus (T2DM) and detracted neighborhood elements in the pediatric population when controlling for race/ethnicity, sex, and socioeconomic status?
- RQ 3: Do demographic characteristics (sex, age, race/ethnicity, socioeconomic status, and family structure), environmental (food insecurity, accessible playgrounds and parks, safe neighborhoods, safe walking paths, accessible recreation centers and presence of detracting neighborhood elements), physical activity, and body mass index (BMI) have an influence on the prevalence of type 2 diabetes among the pediatric population?

This chapter includes the findings from an analysis utilizing secondary data from the NSCH as well as encompassed how the data answers each research question. Following the reiteration of the research questions, their affiliated hypotheses, and the data collection summary; the descriptive data that characterizes the variables from the NCHS will be conveyed. Additionally, this chapter comprises of the statistical analysis results for each research question. Lastly, Chapter 4 concludes with a summary of the study results.

Data Collection

This quantitative secondary data analysis involved the NSCH. The aim of this annual cross-sectional study is to describe the physical and emotional health of non-institutionalized U.S. children aged 0–17 years old (Child and Adolescent Health Measurement Initiative, 2021). Though this survey was created by three federal governmental entities, it is disseminated by the U.S. Census Bureau. The Census Bureau randomly selects households with children under 18 and randomly selects one child from each household, thus creating a nationally representative sample. Between 2019 (June 2019 and January 2020)-2020(July 2020 to January 2021), a total of 72,210 (29,433 and 42,777 in 2019 and 2020 respectively) surveys were completed. The overall weighted response rate for both 2019 and 2020 was 42.4% (Child and Adolescent Health Measurement Initiative, 2021). To obtain access to the secondary data analyzed for this study, a data agreement was signed with the Data Resource Center for Child & Adolescent Health. Before being granted access to the 2019–2020 NSCH, they inquired about the purpose of the data request, the years of data, format of data, and a brief plan on how the data would be utilized. Following approval, a link containing the dataset and codebook was sent.

This data was analyzed in the Statistical Package for the Social Sciences (SPSS) Version 28.0. The 2019–2020 NSCH dataset originally consisted of 826 variables but after using the *delete variable* command, the dataset consisted of the following 14 variables: sex, age, race/ethnicity, socioeconomic status (measured as federal poverty level) , family structure, food insecurity, accessible playgrounds and parks, safe neighborhoods, safe walking paths, accessible recreation centers, presence of detracting neighborhood elements, physical activity, BMI and Type 2 diabetes diagnosis. Some of these variables were manipulated but remained in their original level of measurements. After manipulating the variable and removing all respondents that did not complete the survey in its entirety, the sample size was 34,725.

Descriptive Statistics for Analysis Variables

2019-2020 NSCH Participants

The 2019–2020 NSCH after being cleaned consisted of 34,725 non-institutionalized children, 6–17 years old. Most of the sample consisted of 12–17-year-old respondents (79.0%), male respondents (51.7%), and White, non-Hispanic (68.8%) respondents. Out of the 34,725 respondents, 69.4% reported living in a home with both parents that were married. Additionally, in this sample 41.9% indicated that they live 400% or greater from the federal poverty level (FPL). Of the 34,725 respondents, 74% were categorized as food secure, and almost 73% of the sample reported that they have access to playgrounds and parks. Similarly, 96.9% perceived their neighborhood as safe, and 72% observed that safe walking paths existed in their neighborhood. In addition, almost 46% of the sample conveyed that the recreation centers in their neighborhoods were accessible. In terms of classifying their neighborhood as detracted, 78.5 % did not observe any detracted elements in their neighborhood.

The last three remaining variables in this analysis were exercise, BMI, and T2DM diagnosis. Regarding exercise, 45.6% of the study sample reported exercise optimally (4-5 days or everyday), 42.3% reported their children moderately exercised (2-3 days), and 12.1% conveyed that their children did no type of exercise. The prevalence of overweightness/obesity as measured by BMI percentiles was 28.5% and the prevalence of T2DM was 0.7%. Table 6 provides full descriptive data on the demographic characteristics of the 2019–2020 NSCH respondents.

Table 6

Frequencies of NSCH Participants

Indicator		N	%
Age			
	6-11 years old	7,285	21.0
	12-17 years old	27,440	79.0
Sex			
	Male	17,961	51.7
	Female	16,764	48.3
Race/Ethnicity			
	Hispanic	4,308	12.4
	White, non-Hispanic	23,899	68.8
	Black, non-Hispanic	2,218	6.4
	Asian, non-Hispanic	1,842	5.3
	Other/Multi-racial, non-Hispanic	2,458	7.1
Family Structure			
	Two Parents, Married	24,106	69.4
	Two Parents, Not Currently married	1,747	5.0
	Single Parents	7,526	21.7
	Grandparent Household	992	2.9
	Other family type	354	1.0
Socioeconomic Status (SES)			
	0-99% FPL	3,771	10.9
	100-199% FPL	5,604	16.1
	200-399% FPL	10,811	31.1
	400% FPL or greater	14,539	41.9
Food Insecurity			
	Food Secure	25,687	74.0
	Food Insecure	9,038	26.0
Accessible Playgrounds and Parks			
	Yes	25,257	72.7
	No	9,468	27.3
Safe Neighborhoods			
	Yes	33,644	96.9
	No	1,081	3.1
Safe Walking Paths			
	Yes	25,014	72.0
	No	9,711	28.0
Accessible Recreation Centers			
	Yes	15,837	45.6
	No	18,888	54.4
Presence of Detracting Neighborhood Elements			
	No Detracting Elements	27,272	78.5
	1 Detracting Element	4,887	14.1
	2 Detracting Elements	1,569	4.5
	All 3 Detracting Elements	997	2.9
Exercise			
	No Exercise	4,187	12.1
	Moderate Exercise	14,703	42.3
	Optimal Exercise	15,835	45.6
Body Mass Index (BMI)			
	Normal (Underweight/Normal weight)	24,820	71.5
	Abnormal (Overweight/Obese)	9,905	28.5

Indicator		N	%
Diabetes			
	Yes	240	0.7
	No	34,485	99.3

Results of Analysis

Although not included in a research question, the chi-square (x^2) test of independence was utilized to measure if there is an association between two categorical variables. In addition to running the X^2 test, to quantify those relationships, Cramer V's correlation statistics were reported. Cramer V's correlation was chosen over *Phi* (φ) because many of the variables consisted of two or more levels; for contingencies greater than 2x2, it is recommended to use Cramer V's (Newsoms, 2007). This X^2 test was conducted to determine whether there were relationships between presence of detracted neighborhood elements and the remaining 13 variables included in this secondary data analysis.

In assessing the relationship between the presence of detracted neighborhood elements and the remaining variables, all relationships were statistically significant (distinguished by a p-value < 0.05) except the relationship between the presence of neighborhood detraction elements and gender, $X^2(3) = 1.4$, p-value = .701, Cramer's V = .006. Among all the variables, the strongest relationship with the presence of detracted neighborhood elements were food insecurity and perceived safety. The relationship between food insecurity and presence of detracted neighborhood elements was determined to be statistically significant with a $X^2(3) = 1{,}099.4$, p-value = <.001 and Cramer's V = .178. Additionally, there was a statistically significant relationship between perceived safety and presence of neighborhood detraction; $X^2(3) = 2{,}912.4$, p-value = .000 and Cramer's V = .290. Shown in Table 7 are the results of the X^2 test of independence along with their p-values and Cramer V's statistics.

Table 7

Chi- Square (X^2) Test of Independence

		No Detracting Elements (n = 27272)	1 Detracting Element (n = 4887)	2 Detracting Elements (n = 11569)	All 3 Detracting Elements (n = 997)	$X^2(df)$ Cramer's V	p-value
Age						14.0 (3) .020	.003
	6-11 years old	5624 (20.6%)	1059 (21.7%)	358 (22.8%)	244 (24.5%)		
	12-17 years old	21648 (79.4%)	3828 (78.3%)	1211 (77.2%)	753 (75.5%)		
Sex						1.4 (3) .006	.701
	Male	14128 (51.8%)	2525 (51.7%)	789 (50.3%)	519 (52.1%)		
	Female	13144 (48.2%)	2362 (48.3%)	780 (49.7%)	478 (47.9%)		
Race/Ethnicity						461.2 (12) .067	<.001
	Hispanic	3047 (11.2%)	791 (16.2%)	272 (17.3%)	198 (19.9%)		
	White, non-Hispanic	19449 (71.3%)	2944 (60.2%)	960 (61.2%)	546 (54.8%)		
	Black, non-Hispanic	1555 (5.7%)	413 (8.5%)	138 (8.8%)	112 (11.2%)		
	Asian, non-Hispanic	1412 (5.2%)	331 (6.8%)	65 (4.1%)	34 (3.4%)		
	Other/Multi-racial, non-Hispanic	1809 (6.6%)	408 (8.3%)	134 (8.5%)	107 (10.7%)		
Family Structure						337.8 (12) .057	<.001
	Two Parents, Married	19498 (71.5)	3125 (63.9%)	940 (59.9%)	543 (54.5%)		
	Two Parents, Not Currently married	1230 (4.5%)	342 (7.0%)	97 (6.2%)	78 (7.8%)		
	Single Parents	5503 (20.2%)	1241 (25.4%)	459 (29.3%)	323 (32.4%)		
	Grandparent Household	786 (2.9%)	125 (2.6%)	50 (3.2%)	31 (3.1%)		
	Other family type	255 (0.9%)	54 (1.1%)	23 (1.5%)	22 (2.2%)		
Socioeconomic Status						1033.5 (9) .100	<.001
	0-99% FPL	2508 9.2%)	743 (15.2%)	288 (19.0%)	222 (22.3%)		
	100-199% FPL	3966 (14.5%)	991 (20.3%)	394 (25.1%)	253 (25.4%)		
	200-399% FPL	8392 (30.8%)	1602 (32.8%)	502 (32.0%)	315 (31.6%)		
	400% FPL or greater	12406 (45.5%)	1551 (31.7%)	375 (23.9%)	207 (20.8%)		
Food Insecurity						1846.5 (3) .178	<.001
	Food Secure	21204 (77.8%)	3157 (64.6%)	848 (54.0%)	478 (47.9%)		
	Food Insecure	6088 (22.2%)	1730 (35.4%)	721 (46.0%)	519 (52.1%)		

		No Detracting Elements (n = 27272)	1 Detracting Element (n = 4887)	2 Detracting Elements (n = 11569)	All 3 Detracting Elements (n = 997)	$X^2(df)$ Cramer's V	p-value
Accessible Playgrounds and Parks						86.3 (3) .050	<.001
	Yes	19550 (71.7%)	3718 (76.1%)	1175 (74.9%)	814 (81.6%)		
	No	7772 (28.3%)	1169 (23.9%)	394 (25.1%)	183 (18.4%)		
Safe Neighborhoods						6691.7 (3) .290	.000
	Yes	26929 (98.7%)	4633 (94.8%)	1361 (86.7%)	721 (72.3%)		
	No	343 (1.3%)	254 (5.2%)	208 (13.3%)	276 (27.7%)		
Safe Walking Paths						43.4 (3) .035	<.001
	Yes	19512 (71.5%)	3577 (73.2%)	1121 (71.4%)	804 (80.6%)		
	No	7760 (28.5%)	1310 (26.8%)	448 (28.6%)	193 (19.4%)		
Accessible Recreation Centers						65.3 (3) .043	<.001
	Yes	12182 (44.7%)	2366 (48.4%)	736 (46.9%)	553 (55.5%)		
	No	15090 (55.3%)	2521 (51.6%)	833 (53.1%)	444 (44.5%)		
Exercise						123.4 (6) .042	<.001
	No Exercise	3088 (11.3%)	681 (13.9%)	244 (15.6%)	174 (17.5%)		
	Moderate Exercise	11406 (41.8%)	2143 (43.9%)	712 (45.4%)	442 (44.3%)		
	Optimal Exercise	12778 (46.9%)	2063 (42.2%)	613 (39.1%)	381 (38.2%)		
Body Mass Index						126.3 (3) .060	<.001
	Normal (Underweight/Normal Weight)	19860 (72.8%)	3312 (67.8%)	1027 (65.5%)	621 (62.3%)		
	Abnormal (Overweight/Obese)	7412 (27.2%)	1575 (32.2%)	542 (34.5%)	376 (37.7%)		
Diabetes						17.2 (3) .022	<.001
	Yes	180 (0.7%)	26 (0.5%)	21 (1.3%)	13 (1.3%)		
	No	27092 (99.3%)	4861 (99.5%)	1548 (98.7%)	984 (98.7%)		

Relationship Between Obesity (as measured by BMI) and the Presence of Neighborhood Detraction Elements (Research Question 1)

The first research question aimed to quantify the association between obesity as measured by BMI and the presence of detracted neighborhood detraction elements when controlling for age, sex and race/ethnicity. Since the data collectors only collected BMI percentiles from non-institutionalized children age 6-17 years, those who were <6 years old were removed in this analysis. Since the dependent variable, obesity had two categories: Normal (underweight/healthy weight), and Abnormal (overweight/obese), a binary logistic regression was conducted. Presence of detracted neighborhood elements, age categories, sex and race were entered into the model as predictors of BMI, with normal (underweight/healthy weight) as the reference category. When comparing abnormal (overweight/obese) to normal (underweight/healthy weight), while controlling for age, race/ethnicity and gender, there was a significance association among the primary predictor, presence of neighborhood detraction elements (p>0.05).

With there being significance, the null hypothesis can be rejected indicating that there is an association between obesity and presence of detracted neighborhood elements. Shown in Table 8 are the standardized coefficients, standard errors, degrees of freedom, *p-values*, exponentiated *B* Values, and the 95% Confidence Intervals (C.I). The results in Table 8 showcases that the association between the presence of neighborhood detraction elements and obesity are statistically significant. When controlling for sex, age, and race/ethnicity the ORs and 95% C.I for areas with 1 detracting element, 2 detracting elements and all three detracting elements were 1.230 [1.151,1.315], 1.348 [1.209,1.505], and 1.485 [1.300,1.696], respectively.

Table 8

Binomial Logistic Regression for Association between Obesity (Measured by BMI) and Detracted Neighborhood Elements while controlling or Age Race/Ethnicity and Sex

						95% CI	
Indicators	B	SE	df	Sig	Exp(B)	Lower	Upper
Detracted neighborhood elements							
No detracting elements							
1 detracting element	.207	.034	1	<.001	**1.230**	1.151	1.315
2 detracting elements	.298	.055	1	<.001	**1.348**	1.209	1.505
All 3 detracting elements	.395	.068	1	<.001	**1.485**	1.300	1.696
Age							
6-11							
12-17	-.267	.029	1	<.001	.766	.724	.810
Sex							
Male							
Female	-.333	.024	1	<.001	.717	.683	.751
Race/Ethnicity							
White, non-Hispanic							
Hispanic	.432	.035	1	<.001	1.540	1.437	1.650
Black, non-Hispanic	.606	.061	1	<.001	1.834	1.675	2.007
Asian, non-Hispanic	-.407	.061	1	<.001	.666	.591	.750
Multiracial/Other	.168	.047	1	<.001	1.183	1.079	1.296
Constant	-.700	.029	1	<.001	.497		

Relationship Between T2DM and Presence of Neighborhood Detraction Elements (Research Question 2)

The second research question aimed to determine the association between T2DM and the presence of detracted neighborhood elements while controlling for race/ethnicity, socioeconomic status (SES) and sex. Since the dependent variable, T2DM had only two categories- Yes, Diabetes, No, Diabetes, a binary logistic regression was conducted. T2DM was the dependent variable, presence of neighborhood detraction elements was the independent variable and race/ethnicity, SES and sex were covariates. Similar to research question 1, presence of detracted neighborhood elements, while an ordinal variable was treated as categorical to get an overall measure of association. When compared to those that have T2DM to those who do not have T2DM, while controlling for SES, race/ethnicity, and sex, there was a statistically significant association with presence of neighborhood detraction elements, ($p>0.05$).

With there being significance, the null hypothesis can be rejected indicating that there is an association between obesity and presence of detracted neighborhood elements. Shown in Table 9are the standardized coefficients, standard errors, degrees of freedom, *p-values*, exponentiated *B* Values, and the 95% Confidence Intervals (C.I). The results in Table 9 highlights the association between the presence of neighborhood detraction elements and T2DM while controlling for SES, race/ethnicity and sex as statistically significant for respondents residing in neighborhoods with 2 or more detracting elements. The ORs and the 95 CIs for no detracting elements, one detracting element, two detracting elements and all three detracting elements are 0.781[.516,1.183], 1.904 [1.202,3016], and 1.805[1.017,3.203].

Table 9

Binary Logistic Regression- Association between T2DM and Presence of Detracting Neighborhood Elements when controlling for SES, Race/Ethnicity, and Sex

						95% CI	
Indicators	B	SE	df	Sig	Exp(B)	Lower	Upper
Detracted neighborhood elements							
No detracting elements							
1 detracting element	-.247	.212	1	.244	.781	.516	1.183
2 detracting elements	.644	.235	1	.006	**1.904**	1.202	3.016
All 3 detracting elements	.591	.293	1	.043	**1.805**	1.017	3.203
Race/Ethnicity							
White, non-Hispanic							
Hispanic	-.426	.231	1	.065	.653	.415	1.027
Black, non-Hispanic	.208	.234	1	.374	1.232	.778	1.949
Asian, non-Hispanic	-.944	.455	1	.038	.389	.160	.949
Multiracial/Other	.235	.224	1	.296	1.264	.814	1.963
Socioeconomic status							
0-99% FPL							
100-199% FPL	-.142	.229	1	.535	.868	.554	1.359
200-399% FPL	-.229	.209	1	.273	.795	.528	1.198
400% FPL or greater	-.435	.211	1	.039	.647	.428	.979
Sex							
Male							
Female	-.057	.130	1	.661	.945	.732	1.129
Constant	-4.668	.202	1	<.001	.009		

Predictors of T2DM (Research Question 3)

The third and final research question in this analysis aimed to evaluate which variables were predictors for T2DM in this nationally representative pediatric population. Similar to research question 2, the dependent variable, T2DM consisted of two categories/levels. But unlike research question 2, research question 3 intended to not only quantify the odds ratio of T2DM with the introduction of new variables but compare them across several models. With this intention, a multilevel binary logistic regression was conducted. Specifically, there were four models included in this multi-level binary logistic regression.

Table 10 displays the indicators/variables, the models and their affiliated indicators, odds ratio and the 95% C.I. The first model (Model I) attempted to assess if obesity (as measured by BMI) was a predictor of T2DM and reported a 95% C.I [1.39,2.326], and an odds ratio (OR)=1.798. These findings were determined to be statistically significant based on the confidence interval not including 1.0. The second model (Model II) includes the indicator, BMI from Model 1 and all demographic variables. Equation I show the logistic regression equation for Model 1, where β_0 is the constant and $\beta_1 X_1$ represents the slope of BMI:

$$\Pr(Diabetes) = \beta_0 + \beta_1 X_1$$

Remaining statistically significant in Modell II was BMI with a reported OR=1.745 and 95% C.I [1.341,2.269]. With the addition of the sex variable and males being the reference group, females had a reported OR=0.983 and 95% C.I [0.762,1.1270]. In Model II, age was also included, where 6-11 years old was the referent. When compared to those 6-11 years old, 12-17 years old respondents had an OR=2.206 and 95% C.I [1.476,3.298]. Race/Ethnicity had 5 categories/levels and whites served as the referent. The ORs and 95% confidence intervals for Hispanics, Blacks (NH), Asian (NH) and Mixed/Other (NH) were reported to be 0.646 [0.411,1.017], 1.134 [0.711,1.807], 0.405 [0.166,0.989], and 1.269 [0.816,1.973], respectively. In Model II, the only race/ethnicity that had a statistical relationship with T2DM was Asians, NH. SES measured by federal poverty level (FPL) was also included in Model II.

Similar to race/ethnicity, SES had four levels and 0-99% FPL was the referent. The first level of SES, 100-199% FPL had a reported OR=0.869 and 95% C.I [0.555,1.395]. The second level, 200-399% FPL had a reported OR=0.806, and 95% C.I

[0.532-1.221]. The last level was for respondents who identified as 400% or greater FPL, this group had an OR=0.668, and 95% C.I [0.436,1.024]. The last demographic variable was family structure, which consisted of five levels, with families that had two parents, married being the reference group. The odds ratio and 95% C.I for two parents (not married), single parents, grandparent's household, and other were 0.729 [0.369,1.439], 0.982 [0.709,1.360], 1.896 [1.093,3.287], and 1.436 [0.523,3.941]. Equation II shows the binary logistic regression equation for Model II, which includes the same variables in Model I and β_2X_2 is the slope of the sex variable, β_3X_3 as the slope of the age groups, β_4X_4 as the slope of race/ethnicity, β_5X_5 representing the slope of SES and β_6X_6 representing family structure's slope:

$$\Pr(Diabetes) = Model\ I + \beta_2X_2 + \beta_3X_3 + \beta_4X_4 + \beta_5X_5 + \beta_6X_6$$

Model III consisted of Model I (BMI only) and Model II (BMI+ demographic variables) with the addition of environmental variables. Similar to the prior two models, BMI remained statistically significant with an OR=1.664 and 95% C.I [1.277,2.170]. With the addition of the environmental variables and utilizing males as the reference group, the OR for sex was reported to be 0.975 with a 95% C.I [0.755,1.259]. The OR and 95% C.I for 12-17 years old, when compared to those respondents who were identified as 6-11 years old was 2.225 [1.488,3.327]. By White (NH) being the referent, the ORs and 95% C.I for Hispanic, Black (NH), Asian (NH), and Mixed/Other (NH) were 0.631 [0.400,0.996], 1.135 [0.708,1.818], 0.427 [0.174,1.044], and 1.231 [0.790, 1.917], respectively. Though 0-99% FPL served as the referent group, the ORs and 95% C.I for 100-199% FPL, 200-399% FPL, and 400% FPL or greater were reported to be

0.883 [0.563,1.386], 0.897 [0.589,1.367], and 0.832 [0.531,1.304], respectively. The last variable before the inclusion of the environmental variables was family structure. The reported ORs and 95% C.I for two parents (not married), single parents, grandparent's household and other were 0.687 [0.347,1.359], 0.917 [0.660,1.275], 1.873 [1.078,3.252], and 1.355 [0.493, 3.727], respectively.

Out of the six environmental variables, five only consisted of two levels. As shown in Table 10, when compared to respondents who were food secure, the OR and 95% C.I for T2DM reported was 1.535 [1.142,2.062]. The conveyed OR and 95% C. I for accessible recreation centers was 1.234 [0.929,1.638]. When compared to respondents who lived in areas with accessible parks, the odds ratio and 95% C.I for T2DM was reported as 0.819 [0.583,1.151]. With the inclusion of sidewalks in this logistic regression, the OR and 95% C.I for T2DM was identified as 1.006 [0.728,1.398]. For perceived safety, with respondents who perceived their neighborhood to be safe serving as the referent, the OR and 95% C.I for T2DM was reported as 1.236 [0.673,2.272]. The last environmental variable, presence of neighborhood detracted elements consisted of four levels. With neighborhoods with no detracted elements representing the referent, the ORs and 95% C.I for All 3 detracted elements, 2 detracted elements, and 1 detracted element were reported to be 1.565 [0.855,2.866], 1.721 [1.073,2.760], and 0.746 [0.492,1.134], respectively. Equation III conveys the binary logistic regression equation for Model III, which includes the same variables in Model I, Model II and $\beta_7 X_7$ representing the slope of food security, $\beta_8 X_8$ substituting for the slope of recreation centers, $\beta_9 X_9$ representing the slope of parks, $\beta_{10} X_{10}$ representing the slope of sidewalks,

$\beta_{11}X_{11}$ representing the slope of safety, and $\beta_{12}X_{12}$ substituting for presence of detracted neighborhood elements:

$$\Pr(Diabetes) = Model\ I + Model\ II + \beta_7 X_7 + \cdots + \beta_{10}X_{10} + \beta_{11}X_{11} + \beta_{12}X_{12}$$

The last model, Model IV contains the first three models with the addition of the exercise variable. Similar to the prior two models, BMI remained statistically significant with an OR=1.641 and 95% C.I [1.256,2.144]. With the addition of the exercise variable and utilizing males as the reference group, the OR for sex was reported to be 0.962 with a 95% C.I [0.744,1.245]. The OR and 95% C.I for 12-17 years old, when compared to those respondents who were identified as 6-11 years old was 2.210 [1.476,3.310]. By White (NH) being the referent, the ORs and 95% C.I for Hispanic, Black (NH), Asian (NH), and Mixed/Other (NH) were 0.624 [0.395,0.986], 1.128 [0.704,1.807], 0.421 [0.172,1.030], and 1.225 [0.787, 1.909], respectively. Though 0-99% FPL served as the referent group, the ORs and 95% C.I for 100-199% FPL, 200-399% FPL, and 400% FPL or greater were reported to be 0.879 [0.560,1.380], 0.893 [0.586-1.360], and 0.831 [0.531,1.303], respectively. The reported ORs and 95% C.I for two parents (not married), single parents, grandparent's household and other were 0.685 [0.346,1.355], 0.913 [0.656,1.269], 1.875 [1.079,3.257], and 1.350 [0.491, 3.716], respectively.

As shown in Table 10, when compared to respondents who were food secure, the OR and 95% C.I for T2DM reported was 1.528 [1.137,2.053]. The conveyed OR and 95% C. I for accessible recreation centers was 1.229 [0.926,1.633]. When compared to respondents who lived in areas with accessible parks, the odds ratio and 95% C.I for

T2DM was reported as 0.820 [0.583,1.152]. With the inclusion of sidewalks in this logistic regression, the OR and 95% C.I for T2DM was identified as 1.008 [0.730,1.392]. For perceived safety, with respondents who perceived their neighborhood to be safe serving as the referent, the OR and 95% C.I for T2DM was reported as 1.229 [0.668,2.259]. With neighborhoods with no detracted elements representing the referent, the ORs and 95% C.I for All 3 detracted elements, 2 detracted elements, and 1 detracted element were reported to be 1.566 [0.855,2.867], 1.717 [1.071,2.753], and 0.746 [0.491,1.133], respectively.

Table 10

Binomial Modeling—Predictors of T2DM

	Model I		Model II		Model III		Model IV	
	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI
BMI								
Normal (Underweight/Healthy weight)	1.0	Referent	1.0	Referent	1.0	Referent	1.0	Referent
Abnormal (Overweight/Obese)	**1.798**	1.390-2.326	**1.745**	1.341-2.269	**1.664**	1.277-2.170	**1.641**	1.256-2.144
Sex								
Male			1.0	Referent	1.0	Referent	1.0	Referent
Female			0.983	0.762-1.1270	0.975	0.755-1.259	0.962	0.744-1.245
Age								
6-11			1.0	Referent	1.0	Referent	1.0	Referent
12-17			**2.206**	1.476-3.298	**2.225**	1.488-3.327	**2.210**	1.476-3.310
Race/Ethnicity								
White, non-Hispanic			1.0	Referent	1.0	Referent	1.0	Referent
Hispanic			0.646	0.411-1.017	**0.631**	0.400-0.996	**0.624**	0.395-0.986
Black, non-Hispanic			1.134	0.711-1.807	1.135	0.708-1.818	1.128	0.704-1.807
Asian, non-Hispanic			0.405	0.166-0.989	0.427	0.174-1.044	0.421	0.172-1.030
Mixed/Other			1.269	0.816-1.973	1.231	0.790-1.917	1.225	0.787-1.909
Socioeconomic status								
0-99% FPL			1.0	Referent	1.0	Referent	1.0	Referent
100-199% FPL			0.869	0.555-1.395	0.883	0.563-1.386	0.879	0.560-1.380
200-399% FPL			0.806	0.532-1.221	0.897	0.589-1.367	0.893	0.586-1.360
400% FPL or Greater			0.668	0.436-1.024	0.832	0.531-1.304	0.831	0.531-1.303
Family structure								
Two Parents, Married			1.0	Referent	1.0	Referent	1.0	Referent
Two Parents, Not Married			0.729	0.369-1.439	0.687	0.347-1.359	0.685	0.346-1.355
Single Parents			0.982	0.709-1.360	0.917	0.660-1.275	0.913	0.656-1.269
Grandparents Household			**1.896**	1.093-3.287	**1.873**	1.078-3.252	**1.875**	1.079-3.257
Other			1.436	0.523-3.941	1.355	0.493-3.727	1.350	0.491-3.716
Food security								
Food secure					1.0	Referent	1.0	Referent
Food insecure					**1.535**	1.142-2.062	**1.528**	1.137-2.053
Recreation centers								
Yes					1.0	Referent	1.0	Referent
No					1.234	0.929-1.638	1.229	0.926-1.633
Parks								
Yes					1.0	Referent	1.0	Referent
No					0.819	0.583-1.151	0.820	0.583-1.152

	Model I		Model II		Model III		Model IV	
	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI
Sidewalks								
Yes					1.0	Referent	1.0	Referent
No					1.006	0.728-1.398	1.008	0.730-1.392
Safety								
Yes					1.0	Referent	1.0	Referent
No					1.236	0.673-2.272	1.229	0.668-2.259
Detracted neighborhood elements								
No elements					1.0	Referent	1.0	Referent
1 element					0.746	0.492-1.134	0.746	0.491-1.133
2 elements					**1.721**	1.073-2.760	**1.717**	1.071-2.753
All elements					1.565	0.855-2.866	1.566	0.855-2.867
Exercise								
No							1.0	Referent
Moderate							1.095	0.742-1.616
Optimal							0.932	0.622-1.398

The last variable in this analysis was exercise. This variable consisted of three levels, no exercise, moderate exercise, and optimal exercise. With no exercise serving as the referent group, the odds ratio and 95% C.I for moderate exercise and optimal exercise were 1.095 [0.742,1.616], and 0.932 [0.622,1.398], respectively. Equation 4 conveys the binary logistic regression equation for Model IV, which includes the same variables in Model I, Model II, Model III and $\beta_{13}X_{13}$ representing the slope of the exercise variable:

$$\Pr(Diabetes) = Model\ I + Model\ II + Model\ III + \beta_{13}X_{13}$$

Summary

A Chi Square Test of Independence was conducted to not only determine the relationship between the presence of neighborhood detraction elements and the included demographic variables, environmental variables, BMI, physical activity and T2DM but to quantify the strength of that association with Cramer's V effect size statistic. Although the Cramer's V effect size statistics varied per variable, only the sex variable did not have a statistically significant relationship with presence of detracted neighborhood elements.

The first research question was used to determine the relationship between obesity, as measured by BMI and the presence of detracting neighborhood elements while controlling for age, sex, and race. To evaluate and possibly quantify the relationship, a binary logistic regression was utilized where obesity was the dependent variable, presence of detracting neighborhood elements was the independent variable and the covariates were age and race. The findings indicated that there was a statistically significant association between obesity and presence of detracted neighborhood elements when controlling for age, sex, and race.

The second research question was used to determine the relationship between T2DM and the presence of detracting neighborhood elements while controlling for race/ethnicity, socioeconomic status (SES) and sex. Similar to the first research question, to understand the relationship a binomial logistic regression was conducted, where T2DM was the dependent variable, the presence of detracting neighborhood elements was the independent variable and the covariates were race/ethnicity, SES, and sex. Like research question one, the findings conveyed that there was a statistically significant relationship between T2DM and the presence of detracting neighborhood elements while controlling for race/ethnicity, SES and sex.

The third research question evaluated predictors of T2DM in this pediatric population. To assess the influence of multiple independent variables on the odds of T2DM diagnosis, required a multiple binomial logistic regression where T2DM was the dependent variable and the remaining 13 variables were predictors. This multiple binomial logistic regression consisted of four models. The first model assessed only BMI and T2DM, the second model included the first model with the addition of demographic variables, the third model consisted of the first two models with the inclusion of environmental variables and the last model included the first three models with the addition of an exercise variables. The findings indicated that predictors of T2DM in this pediatric population were abnormal weight status (overweight/obese), 12-17 years old, not having Asian or Hispanic ancestry, living with grandparents, being food insecure and living in a neighborhood with at least two detraction elements. In Chapter 5, these findings will be interpreted, limitations will be discussed, future directions/recommendations are conveyed as well as how these results can be applied to promote social change.

Chapter 5: Discussion, Conclusions and Recommendations

The purpose of this research study was to determine predictors of T2DM and to evaluate the association between T2DM, obesity, and the presence of detracted neighborhood elements. These relationships were studied cross-sectionally in the pediatric population utilizing the 2019–2020 NSCH. This study was conducted to enhance public health research examining the relationship between policy, location, and health outcomes. Additionally, I conducted the study to fill the gaps regarding the impact that neighborhood detraction may have on obesity and T2DM susceptibility and severity in the pediatric population. In this chapter, the findings will be presented and interpreted, study limitations are conveyed, recommendations are presented, and social implications are described.

Summary and Interpretation of the Findings

There were three research questions examined to determine whether obesity and T2DM were associated with the presence of neighborhood detraction elements and predictors of T2DM in the pediatric population. Additionally, a chi-square test of independence was used to see if there were any relationships between neighborhood detraction and all the variables included in this analysis. In Chapter 2, the literature review explained the role of neighborhood-built environment with health outcomes, severity, susceptibility, or expenditures (CDC, 2018; Hu et al., 2018; Roeder, 2017). The crux of this analysis is that as a result of redlining, neighborhoods were disinvested and because of these transgenerational disinvestments, neighborhood detraction may have exasperated poorer health outcomes for the inhabitants. As stated in Chapter 2, it has been posited that neighborhood-built environment may explain 10% of variation in health outcomes (Magnan, 2017).

The findings in this analysis support that neighborhood-built environment in the form of neighborhood detraction is associated with factors that influence health outcomes, specifically overweightness/obesity and T2DM. The results of the chi square test for independence show that 12 of the 13 variables were statistically significant. To measure their effect size, Cramer's V statistic was used to quantify their association.

Based on Akoglu, the interpretation for Cramer's V effect sizes is as follows, ">0 (No or very weak), >0.05 (weak), >0.10 (Moderate), >0.15 (Strong) and >0.25 (Very Strong)" [Akoglu, 2018]. Aforementioned, that amongst the demographic variables- age, race/ethnicity, family structure, and SES were the only variables that reported a statistically significant association with the presence of detracted neighborhood elements. Although age was statistically significant, there was a reported effect size of .020, which can be interpreted as no effect/very weak effect. Similarly, the relationship between race/ethnicity and the presence of detracted neighborhood elements were reported to be statistically significant but reported an effect size of .067. The strength of this association between the variables are weak. With a reported Cramer's V statistic of .057, the relationship between family structure and the presence of detracting neighborhood elements is a weak association. The last demographic variable with a reported statistically significant association with presence of detracted neighborhood element was SES. With a reported Cramer's V statistic of .100, this association can be interpreted as moderate.

There were five environmental variables used in this analysis, which all had a statistically significant association with the presence of neighborhood detracted elements. With a reported Cramer's V statistic of .178, the relationship between food insecurity and detracted neighborhood elements is considered strong. Accessible playgrounds and parks reported a Cramer's V statistic of .050, which can be interpreted as a weak association. The strongest association among all variables in this analysis was perceived safety with a conveyed Cramer's V statistic of .290. Both safe neighborhoods and safe walking paths were interpreted as very weak associations with reported Cramer's V statistics .043 and .042, respectively. Exercise while statistically significant was interpreted as having a very weak association with neighborhood detraction elements. The Cramer's V statistic for BMI was recorded as.060, which would infer a weak association with detracted neighborhood elements. Lastly, the association between T2DM and the presence of neighborhood detracted elements was reported numerically as .022 which substitutes for a very weak association.

Essentially, the results of the X^2 test for independence report how independent the presence of neighborhood detracted elements are with the aforementioned variables, with Cramer's V statistic quantifying that relationship; confined by the parameter of 0 (independent) to 1(perfect association; Kim, 2017). Considering the statistically significant relationships and varying effect sizes between presence of detracted neighborhood elements and the aforementioned variables, the only two variables with a strong association were perceived safety and food insecurity. Policies and initiatives should be crafted around these two indicators/elements in not only identifying detracted neighborhoods but reversing the impact, thus reinvesting into underserved or detracted communities.

Although many of the relationships between the presence of detracted neighborhood elements and the other variables were weak, they should also be included in initiatives and interventions. These results could be used to describe characteristics of neighborhoods suffering from various levels of detraction. In interpreting the results of the X^2 test for independence and Cramer's V statistic, it should be acknowledged that both statistical significance and effect size are dependent on sample size and standard deviation, respectively. As conveyed earlier, detracted neighborhoods are associated with food insecurity, less perceived safety, less walking paths/green space etc. (McCullough, 2022; Powell, 2021). Not only did majority of this sample report what the literature deemed as protective factors from obesity, and T2DM but they essentially reported living in the complete opposite characteristics of what the literature has stated is associated with neighborhood detraction. Further, among the levels of neighborhood detracted the data were dispersed. So, expectedly that while the environmental variables are statistically significant, their effect sizes are not as strong because having access to parks and recreation centers are not characteristics of neighborhood detraction.

The variables in this analysis also include risk factors from a biological and environmental lens. Like most chronic conditions there are many etiologic factors that contribute to pediatric obesity (Reis et al., 2020). Although there are many factors that influences the susceptibility, severity and health-related conditions associated with obesity, the two most common causes are sedentary lifestyle and poor diet (CDC, 2012). In most of the literature, the indicator of obesity is food insecurity with emphasis being placed on food swamps and food deserts. These findings support the literature where areas historically redlined, areas with higher concentrated disadvantage have a higher prevalence of obesity when compared to more affluent areas (Gorski et al., 2018; Kong et al., 2022; Trangenstein et al., 2020). In this analysis, when controlling for age, sex, and race/ethnicity, when compared to those that reside in neighborhoods with no detracted elements, there was a 23%, 34.8% and 48.5% increase in odds of obesity among those who lived in areas with one detracted element, two detracted elements, and all three detracted elements, respectively.

These findings not only convey the relationship (although multifactorial) between neighborhood detraction and obesity, it almost mimics a dose-response relationship where as the number of elements increase so does the odds of being overweight/obese. Although this analysis is not able to prove direction of the association/temporality, there was almost 26% increase odds from being exposed to just one detracted element to all three detracted elements. Though neighborhood detraction in this analysis only focuses on litter, vandalism and abandoned houses, supermarket redlining occurs when corporations and vendors deem an area risky (Shaker et al., 2022). Litter, vandalism, abandoned houses not only speak to the aesthetics of an environment/neighborhood but can become the characteristics of that environment (Padcrush, para.1).

Similar to obesity, T2DM is a chronic condition that has many risk factors, with the two most documented being sedentary lifestyle and poor diet (Raman, 2016). The findings of this study support the current literature that acknowledges not only the impact the environment has on T2DM but even the heterogeneity among cases of T2DM (Boule et al., 2001; Creatore et al., 2016; den Braver et al., 2018; Hajna et al., 2016). Although not statistically significant, when controlling for race/ethnicity, sex, and SES, respondents living an area with no detracted elements had a 0.781 decrease in odds of having T2DM. Further, when compared to those who live in a neighborhood with no detracting elements, there was a statistically significant 90.4% increase in odds of T2DM among those who reside in a neighborhood with at least two detracting neighborhood elements. Lastly, when compared to respondents who inhabit neighborhoods with no detracting elements, those that live in neighborhoods with all three detracting elements have a statistically significant 80.5 increase odds of T2DM.

Unlike the results of RQ 1, the relationship between the presence of neighborhood detraction and T2DM does not mimic a positive correlation. Although when compared to those who live in a neighborhood with no elements the odds are greater amongst those who live in a community where elements are exhibited in a community. These odds appear even higher when compared to the reported odds of obesity; there was almost an 80% in odds between those who reside in a neighborhood with one element when compared to those who live in a neighborhood with all three elements. Though this analysis was not able to measure temporality or pinpoint a mechanism, neighborhood-built environment should be considered not only in diabetes prevention but diabetes management. It would posited that the decrease in odds of T2DM between residing in a neighborhood with two elements and three elements existed because of sample size as well as dispersion.

The nexus between pediatric obesity and T2DM has been established with biological plausibility to establish temporality and how cases of T2DM may significantly differ between demographic groups (CDC,2017). To evaluate the predictors of T2DM in this pediatric population a multi binomial logistic regression was conducted. This analysis found the predictors of T2DM in this pediatric population as being overweight/obese, 12-17 years old, living with grandparents, food insecure and living in a neighborhood with the presence of two detracting elements. In Model I, which only consisted of the BMI variable, when compared to those who were either underweight or at a healthy weight, those that were overweight or obese had a statistically significant 79.8% increase in odds of having T2DM. Although this variable decreased with the inclusion of other variables for the remaining models, it remained statistically significant. In Chapter 2, I discussed that the CDC reported demographic variables such as race/ethnicity, age, sex and SES are risk factors for T2DM (CDC, 2017). Model II of this multi binomial logistic regression included similar variables. With the inclusion of the demographic variables (sex, age, race/ethnicity, SES, and family structure), the odds of T2DM in those who were overweight/obese decreased from 79.8% (Model I) to 74.5%, when compared to those who were either underweight or at a healthy weight. In the final model, containing all the variables, when compared to those of underweight/ healthy weight, respondents that were overweight/obese 64.1% increase in odds of T2DM.

Although most of the literature acknowledges that T2DM can be diagnosed in childhood/teenage years the risk factor starts at 35 years old with the caveat of genetics/family history and prediabetic diagnosis (CDC, 2017), the results of this analysis indicate that when compared to children 6-11 years old, children 12-17 years old have a

120.6% increase in odds of T2DM. Unlike evidence reported in Chapter 2, this analysis reports that being Hispanic and Asian, Non-Hispanic had a protective factor as a predictor in T2DM (Lawrence et al., 2021; Jensen & Dabelea, 2018). The CDC reports that a risk factor for T2DM is having African ancestry or identifying as Hispanic (CDC,2017). While Hispanic only was statistically significant in Model III and Model IV; Asian, NH was statistically significant in all models. Interpretationally, Hispanics had a 0.624 decrease of odds of T2DM when compared to White, NH. Similarly, those who identified as Asian, NH had a 0.421 decrease in odds of T2DM. The disagreement in findings between this analysis and the previous literature could represent that the mechanism between racial/ethnic susceptibility and T2DM furtherly needs to be studied. In considering the previously mentioned caveat about statistical significance and effect size, this new finding could convey or report that Hispanics may have been furtherly acclimated into the economy, thus having better opportunities to reach optimal health (excluding illegal immigrants). In terms of family structure, it was reported that when compared to families with two married parents, respondents living with their grandparents had an 87.5% increase of odds of T2DM. Additionally, it was reported that when compared to those who identified as food secure, those who were food insecure had almost a 53% increase in odds of T2DM. There is robust literature that shows similar results (Elberl et al., 2020, Fiechtner et al., 2015; Kral et al., 2017, Oberle et al., 2019).

Albeit these findings are supported by previous literature, this analysis surpasses what has already been establish by attempting to characterize the intermediate step of neighborhood detraction as a presumable result of redlining. As mentioned in Chapter 2, the two most common risk factors for both overweightness/obesity and T2DM is poor diet and a sedentary lifestyle where the common themes/constructs were food insecurity (in the form of food deserts and food swamps) and a lack of physical activity (presented as lack of greenspace and walkability). In research questions 1 and 2, these findings newly quantify the relationships between neighborhood detraction, overweight/obesity and T2DM in pediatrics. In research question 3, this analysis aims to describe predictors of T2DM in the pediatric population. These findings are new and informative because to my knowledge outside of medical history and maybe genetics, there has never been a reported association between family structure, specifically living with grandparents alone. Additionally, living in a neighborhood with at least two elements of neighborhood detracted was newly discovered. These new findings solidify the relationship between current neighborhood-built environment, and health outcomes.

Lastly, these findings reassure why the social determinants of health (SDOH) is a fundamental theory of public health. The findings utilize neighborhood-built environment, economic stability, and social community context in the form of variables included in the 2019-2020 NSCH. These results encompass those three domains through an environmental perspective to assess not only how these social conditions can be shaped by the neighborhood in which one lives (X^2 Test of Independence, research questions 1 and 2) but how those often overlapping and intersectional domains may influence health outcomes (research question 3). Specifically, the analysis for research question 3, intentionally and quantifiably highlights the ideology of SDOH while unintentionally showcasing racial heterogeneity, which presumably may have been caused or is associated by the transgenerational implications of redlining, currently presented as neighborhood detraction.

Theoretical Methods

The social determinants of health (SDOH) is a staple in the field of Public Health. This theoretical model is often used to assess and evaluate causal factors of health outcomes, inequities and disparities. Although this study includes variables that public health professional cannot control (age, race/ethnicity), the findings in this analysis takes a primordial prevention perspective to assess the root contributors/predictors of obesity and T2DM. For example, food insecurity was found to not only be a predictor of T2DM, but has a strong association with neighborhood detraction. To promote a healthy lifestyle means having access to affordable, and fresh healthy options. The SDOH as a model posits that these 5 domains (economic stability, quality education, access to quality healthcare, social community and context, and neighborhood built and environment) work intersectional and simultaneously to characterizes a person's health outcomes. The intersectionality of the variables included in this analysis mimics the ideology behind this theoretical model. Although some of the results were unexpected, the findings of this analysis captured economic stability, social and community context, and neighborhood-built environment in a diverse pediatric population.

Based on the literature, some of the results that were unexpected were stronger associations (presented as Cramer's V statistics) between the presence of detracted neighborhood elements and the environmental variables, as well as obesity, T2DM. Additionally, another unexpected result was while the direction of odds ratios was expected with the inclusion of new variables, more variables were expected to be statistically significant based on the literature. These two statements of unanticipated findings should be caveated. In terms of the Cramer's V statistics, effect sizes are dependent on standard deviation or how dispersed the data is (Sullivan & Feinn, 2012). Furtherly, statistical significance is dependent on sample size which is why *p-value* is insufficient (Sullivan & Feinn, 2012)

Limitations of the Study

As previously discussed in Chapter 1, there are limitations with this research study's findings. First, this study was a secondary data analysis, utilizing a dataset from the National Survey of Children's Health (NSCH); therefore, there were limitations due to the use of fixed questions from the survey. For example, the original exposure/independent variable in this analysis was areas historically redlined but because that variable was not included in this secondary dataset nor was it feasible to request that confidential data, the presence of detracted neighborhood elements, a well-documented result of redlining and disinvestment was utilized as a proxy variable. Secondly, the data utilized in this analysis was collected through a questionnaire in which the parent's answered about their children; this type of data collection is vulnerable to recall and misclassification bias.

Thirdly, the only respondents in the NSCH are children who are non-institutionalized and live in a household. This excludes children and families that may experience homelessness, thus not being totally generalizable. Another limitation of this analysis was the distribution of the T2DM outcome variable and several other variables, which may have impacted the interpretation of variables that have been well documented to be associated with T2DM. While this current study focused on economic stability, social and community context, and neighborhood-built environment domains under the social determinants of heath, it did not include other factors that have been shown by previous research to be associated with overweightness/obesity and T2DM. For example, housing quality, hours of sleep, health status of parents, mental health conditions/contributors (stress, anxiety) or quality and access to health care services (Balentine, 2015; CDC, 2012). The exclusion of these variables may not fully capture the multifactorial nature of obesity and T2DM. Lastly, this analysis was conducted cross-sectionally. Cross-Sectional research designs are not able to determine temporality.

Recommendations for Future Research

While no study is perfect and limitations may exist, with conducting a literature review, gaps in the literature may be revealed. In Chapter 1 it was reported that a major assumption of this analysis was that not only was redlining still occurring, but the transgenerational implications of redlining were still being observed in major cities. To my knowledge, there is no research that assess the relationship between T2DM or obesity prevalence in the pediatric population with areas historically redlined. Focusing on redlined areas and the potential implications it may have on pediatric outcomes, can be seen as the real-world application of the social determinants of heath as it captures the first two core functions of pubic heath, assessment and policy development. Another assumption mentioned in Chapter 1 was that neighborhood detraction and redlining are potentially related. To solidify this assumption, in the future it would be ideal to not only test that association but use historically redlined areas as the primary exposure. This will require the utilization of ArcGIS, a mapping software, access to the original Housing Owner Loan Corporation (HOLC) maps and US Census data. In this future analysis, I would like see and the reporting of the overlapping of current US Census tract data and HOLC maps to see which areas that were historically redline are currently redlined. Every city, every neighborhood and every street have a unique arbitrary numerical identifier.

In the future, I would like to receive access to the non-public version of this dataset and conduct a nationally aggregation of areas historically redlined, obesity and T2DM with the same dataset and same variables. Not only will this solve the assumption made previously but it would be original in the sense that it has not occurred and it could bring awareness to some scholars would say that redlining still occurs and impact today's society (Columbia Broadcasting Services, 2020; Smith et al,2019). Additionally, as previously mentioned this excluded some well establish risk factors that may increase susceptibility of overweightness/obesity and T2DM because of availability. In future analyses, to furtherly understand the multifactorial and complex relationship about T2DM and obesity, if accessible these variables should be considered. Similar to aforementioned, evaluating the relationship between these indicators and potential differences across either neighborhood detraction or areas historically redlined could furtherly convey the nexus between location, policy and health outcomes. Lastly, as implied earlier, in the future and using the same methodology, I would like to conduct the same analysis in a sample that reports more associated characteristics of neighborhood detraction. Furtherly, to contribute to the literature, it should be considered to explore establishing temporality by analyzing similar relationships in a cohort or longitudinal study.

Implications for Social Change

It is well documented that as the prevalence and incidence of overweightness/obesity in the pediatric population increased, the number of T2DM cases has increased (CDC,2021; Lawrence et al., 2021; Sanyaolu et al., 2019). Furtherly, it has been acknowledged that amongst these cases of both chronic but preventable conditions, there are significant demographic differences amongst cases, resulting in health disparities (CDC,2017). Understanding the relationship between location, policy and health outcomes is pivotal in creating health equity and social justice on all levels. On an individual level the results of this analysis can bring awareness of primordial, primary and secondary levels of prevention. The results of this analysis report the indicators of T2DM as well as the relationship between obesity, T2DM and presence of neighborhood detraction elements. In conjunction with the established literature, understanding the risk factors for both conditions and preventing those risk factors from developing can be the first step to decreasing health disparities. The social implication of these findings can be used to create neighborhood-built environment initiatives such as community gardens, which have been shown to not only improve eating habits but promote a sense of community (Castro et al., 2013; Hume et al., 2022). Another program that could be implemented could include creating walking clubs, exercise classes that have also shown great results (Baker et al., 2015). On an interpersonal and intrapersonal level these findings can be used to encourage behavior changes; with the intention to minimize those risk factors primordially as well as those that have already developed. These behavior changes resemble activities such as glucose monitoring, encouraged daily exercise for 30 minutes as well as consuming nutrient foods. Considering everything, a social implication of these findings is the acknowledgement of a neighborhood-built environment and social class health disparity that does not have to exist.

Because of the political structure of our society, to create social change requires not only individuals being leaders in their communities, but a collection of communities holding political officials accountable via townhall meetings, letters or the voting polls. This research might be used to encourage individuals to vote in their best interest. The three core functions of public health are assessment, policy development and assurance. The results of this analysis can serve as the assessment needed to create effective and sustainable interventions (monthly fresh food markets, allocating money for recreation center complex construction or extending hours, building parks, incentivizing lowering carbon foot prints etc.) to not only decrease the prevalence and incidence of T2DM but prevent those root causes from occurring. A great example of this is the former First Lady, Michelle Obama focusing on childhood obesity and not only changing the nutritional value being given in U.S public schools but promoting physical activity (Batchelder & Matusitz, 2014).

Like other fields/industries and because of our capitalistic society, Public Health requires funding; those funds have to be allocated to those detracted communities to promote health equity and social justice. Moreover, the findings in this analysis can speak to legislators and politicians to provide the services needed to remain elected since their priorities and voting should reflect the needs and wants of their constituents. To understand their constituents can lead to an increased awareness of daily challenges (latchkey children [children that are left alone or without parent supervision to take care of themselves for a substantial part of the day[Leung et al., 1996]] , food insecurity etc.) which ultimately can lead to investments that work within the limitations of those detracted areas and could also fix neighborhood detraction associated problems such as crime (Rundle et al., 2009; Sugalia et al., 2016; Wei et al., 2021). Crime (measured subjectively or objectively) has been shown to influence levels of physical activity (Lenhart et al., 2017; Rees-Punia et al., 2018). Investing or reinvesting in detracted neighborhoods does not have to be solely financial, it can be educational (cooking demonstrations etc.), creating/promoting workforce development programs, considering community policing, promoting affordable community development and supporting programs such as Buy Black the Block. To invest or reinvest in detracted neighborhoods means to reinvest in the people, the culture who ultimately at optimal health are able to contribute to the economy.

Conclusions

In summary, the literature provided evidence that amongst all the variables included in this analysis although varying in effect sizes, the presence of neighborhood detraction elements was strongly associated with food insecurity and safe neighborhoods. This research illustrated the statistically significant relationships amongst obesity, T2DM and the presence of neighborhood detraction elements. Lastly this research suggested that the predictors of T2DM were overweight/obese weight classification, 12-17 years old, living with grandparents, food insecure and living in a neighborhood exhibiting the presence of at least two detracting elements. Continued research is needed to strive for health equity and social justice amongst the most vulnerable populations as well as understanding the complex relationship between overweightness/obesity and T2DM. Assessing and evaluating the nexus between location, policy and pediatric health outcomes is pivotal for the U.S economy as the future generations will become the primary contributors.

Establishing the root causes of heath disparities, presented in social conditions that can be characterized by one's environment is the first step in reducing/eliminating health disparities. Understanding the mechanism between environment and health outcomes require the dismantling of structural policies and acknowledging how the atrocities of the past impact the future and how they are being experienced presently. To rectify detracted neighborhoods requires investing into the physical component of the neighborhood as well as the people and the culture so that health equity and social justice are not such vague concepts only believed to be reach by those deemed desirable.

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