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Area-Level Factors Linked to Obesity in African American and Caucasian Women in Michigan

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Abstract

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by

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Abstract

Obesity is a major public health crisis, affecting every segment of the U.S. population. African American women have higher prevalence of obesity than all other subpopulations and are disproportionately burdened by the disease and its comorbidities. Despite this disparity, African American women are often underrepresented in obesity research. This research examined obesity-related risk factors specific to African American women compared to those for Caucasian women. The design was based on the socioecological model and social cognitive theory, both emphasizing the impact of social factors on health outcomes. The data set included only adult Michigan women from the NHANES study. Multiple logistic regression analyses were conducted for each race (African American and Caucasian), with obesity status as the outcome; area-level factor residence status, the main predictor; and age, education, and income the controlling factors. The results indicated that residence status is a major predictor of obesity for African American women, with renters having an increased ($OR = 1.501$, $p = 0.025$) odds relative to homeowners. In contrast, for Caucasian women, income ($p = .000$), and education ($p = .011$) were both significant, but residence status was not ($p = .237$). These results highlight the differences between African American and Caucasian women's obesity risk factors and emphasize the importance of researching obesity in African American women separately. The positive social impact includes developing obesity interventions and health education programs that address the social factors involved.

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Chapter 1: Introduction to the Study

Introduction

Obesity is a chronic debilitating condition existing in epidemic portions worldwide (Arroyo-Johnson & Mincey, 2016; Ng et al., 2014). The highest prevalence of obesity is seen within the United States (Arroyo-Johnson & Mincey, 2016). The etiology of obesity is multifactorial and complex. These factors originate from individual (intrapersonal), community (interpersonal), environmental (area level), policy, gender, race, and genealogy (pedigree; Arroyo-Johnson & Mincey, 2016; Pozza & Isidori 2018; Tallon et al., 2018). Obesity is associated with health behaviors and health outcomes, such as Type 2 diabetes (T2D), hypertension, dyslipidemia, stroke, coronary heart disease, osteoarthritis, sleep apnea, respiratory disease, certain types of cancer and even all-cause mortality (Arroyo-Johnson & Mincey, 2016; National Heart, Lung, and Blood Institute, 2013).

Obesity burden exists across people of all races and ethnicities, age groups, genders, and socioeconomic statuses in the United States (Ogden, Carroll, Fryar, & Flegal, 2015). For instance, in Detroit, Michigan, the number of people living with obesity is higher than in many other cities in the state of Michigan (Koh, Grady, Darden, & Vojnovic, 2017). Obesity prevalence is higher in the city of Detroit and surrounding suburbs (Koh et al., 2017; Koh, Grady, & Vojnovic, 2015; State of Obesity, 2018). According to the 2013 to 2015 Behavioral Risk Factor Surveillance System (BRFSS) data, 30–35% of obese adults were reported in Michigan (Fussman, 2015. Currently, Michigan ranks 16th on obesity burden (31.2%) among the 50 states in the United States (State of Obesity, 2018). In 2015, about 35.1% of adults ages 45–64 years were obese in Michigan (Fussman, 2015). In 2016, according to BRFSS data, 32.5% of adults in Michigan were obese with a body mass index (BMI) ≥ 30, and 35% are overweight

(BMI 25–29.9; Fussman, 2015; State of Obesity, 2018). In Michigan, roughly 37.6% of African Americans are obese (Fussman, 2015; Johnston, Lee, & Johnston, 2011; State of Obesity, 2018).

The multifactorial etiology of obesity has been widely studied; however, comparative assessment of obesity risks based on Income level, nutrition, physical activity, education level, employment status, age, gender, and geographic area between African American and Caucasian women has not been explored (Johnston et al., 2011; Kumanyika, Whitt-Glover, & Haire-Joshu, 2014; Rosenbaum, Piers, Schumacher, Kase, & Butryn, 2017; State of Obesity, 2018). Also, African Americans are mostly underrepresented in weight loss studies (Kumanyika et al., 2014; Rosenbaum et al., 2017) making a research study such as this necessary for the community.

According to Arroyo-Johnson and Mincey (2016), risk factors for obesity are energy imbalance between nutrition and physical activity (i.e., between consumption and expenditure), direct and indirect genetic effects, gene-environment interactions, and social determinants of health. Investigating the relationship between an area-level (homeownership: rent or own) environmental factor and obesity among African American and Caucasian women, while controlling for age, gender, and income, is a significant public health effort, potentially useful toward changing existing policy or toward developing interventions against obesity or toward augmenting health promotion.

In Chapter 1, I present a summary of the cross-sectional quantitative study I intend to conduct. In the background section of Chapter 1, I include known evidence relating to obesity prevalence and risk factors. I reiterate the current gap in the literature, and I justify the need for this research. Chapter 1 also includes the problem statement and the significance and relevance of this study for public health in Michigan. In Chapter 1, I also link the research problem with the purpose of the study, as well as the dependent and IVs. Chapter 1 also includes the research questions and hypotheses and the type of theoretical foundation used to guide my research. Conceptual definitions, the nature of the study, assumptions, study scope, and limitations are also part of Chapter 1. Finally, Chapter 1 concludes with a section on study significance and a summary.

Background

Obesity burden exists across people of all races, ethnicities, age groups, genders, and socioeconomic statuses in the United States (Ogden et al., 2015). For instance, in Detroit, Michigan, the number of people living with obesity is higher than in many other cities in the state (Koh et al., 2017). Obesity prevalence is higher in the city of Detroit and surrounding suburbs (Koh et al., 2017; Koh et al., 2015; State of Obesity, 2018). According to the 2013–2015 BRFSS data, 30–35% of obese adults were reported in Michigan (Fussman, 2015). Currently, Michigan ranks 16th in obesity burden (31.2%) among the 50 states (State of Obesity, 2018). In 2015, about 35.1% of Michigan adults ages 45–64 years were obese (Fussman, 2015). In 2016, according to BRFSS data, 32.5% of adults in Michigan were obese with a BMI ≥ 30, and 35% were overweight (BMI 25–29.9; Fussman, 2015; State of Obesity, 2018). In Michigan, roughly 37.6% of African Americans are obese (Fussman, 2015; Johnston et al., 2011; State of Obesity, 2018). Though the multifactorial etiology of obesity has been widely studied, comparative assessment of obesity risks based on income level, nutrition, physical activity, education level, employment status, age, gender, and geographic area between African American and Caucasian women has not been explored (Kumanyika et al., 2014; Rosenbaum et al., 2017; State of Obesity, 2018). Also, African Americans are underrepresented in weight loss studies (Kumanyika et al., 2014; Rosenbaum et al., 2017), thus supporting the need for this study.

According to Arroyo-Johnson and Mincey (2016), obesity risk factors include energy imbalance between nutrition and physical activity (i.e., food consumption and expenditure), direct and indirect genetic effects, gene-environment interactions, and social determinants of health. Therefore, examining the relational links of area-level factors, such as homeownership (rent or own), and environmental determinants to obesity among African American and Caucasian women while controlling for age, and income will contribute immensely to important public health efforts. The findings could inform existing policy and intervention approaches for obesity.

Income is a confounding variable influencing obesity prevalence (Fan, Wen, & Kowaleski-Jones, 2016; Kim, Wang, & Arcan 2018). Education attainment is one determinant of income earnings (Kim et al., 2018). An individual's income can also determine an area level (environmental) factor such as housing tenure (i.e., own or rent status) and the type of housing tenure choices (Kim et al., 2018). In other words, an individual's income level influences the decision-making processes in terms of community housing selection for residence. Kim et al. (2018) explored the association of income inequality and obesity in New York. Economic factors, poverty, and income inequality influenced health outcomes and obesity prevalence across New York state (Kim et al., 2018). Further studies should explore potential area-level factors that contribute to the differing geographical effects of income inequality on obesity (Kim et al., 2018).

Research has shown that low-income African American women in certain communities, especially rural areas, may be susceptible to a higher risk (80%) for obesity-related adverse outcomes like T2D (Heisler, 2017). The African American community in Michigan is considered an underserved population (Salihu et al., 2015). The findings of this study may positively influence public health interventions to reduce and prevent high prevalence of obesity among the selected target population and the rest of the population. Other studies on obesity have been conducted to identify such high need population groups in order to provide targeted care. Salihu et al. (2015) proposed the utility, applicability, and validity of a community priority index to determine priority areas of need in a community-based participatory research to maximize public health efforts on obesity prevention and reduction.

In addition, Salihu et al. (2015) suggested that identifying high need communities is important for resource allocation based on priority need, community integration, and time management. Communities in Michigan with poor housing tenure and high obesity prevalence could be identified via a community-based participatory research approach. Salihu et al. (2015) also proposed that obesity prevention programs can use a community-based participatory research approach to provide services to underserved and priority communities. Although an instrument such as community priority index will not be applied in this study, the use of community priority index to allocate resources for obesity preventive efforts is important because it addresses the unmet needs of a selected target population (Salihu et al., 2015).

Lack of physical activity is a contributing risk factor for obesity (Kumanyika et al., 2014; Rosenbaum et al., 2017; Johnson et al., 2011). Physical activity influences obesity at individual and environmental levels. Heath et al. (2012) examined the role of social support within communities to boost the effectiveness of physical activity. Heath et al. (2012) provided key information on how social support is instrumental to individual and community well-being and perhaps how it influences some aspects of area-level factors. The study only focuses on an area level factor such as rent or own status; however, other aspects of the environment, including social support or physical activity, may influence obesity as well.

Problem Statement

Obesity burden exists across people of all races, ethnicities, age groups, genders, and socioeconomic statuses in the United States (Ogden et al., 2015). For instance, in Detroit, Michigan, the number of people living with obesity is higher than in many other cities in the state (Koh et al., 2017). Obesity prevalence is higher in the city of Detroit and surrounding suburbs (Koh et al., 2017; Koh et al., 2015; State of Obesity, 2018). According to 2013–2015 BRFSS data, 30–35% of obese adults were reported in Michigan (Fussman, 2015). Currently, Michigan ranks 16th on obesity burden (31.2%) among the 50 states in the United States (State of Obesity, 2018). In 2015, about 35.1% of adults ages 45–64 years were obese in Michigan (Fussman, 2015). In 2016, according to BRFSS data, 32.5% of adults in Michigan are obese with BMI ≥ 30, and 35% are overweight (BMI 25–29.9; Fussman, 2015; State of Obesity, 2018). In Michigan, roughly 37.6% of African Americans are obese (Fussman, 2015; Johnston et al., 2011; State of Obesity, 2018). Although the multifactorial etiology of obesity has been widely studied, comparative assessment of obesity risks based on income level, nutrition, physical activity, education level, employment status, age, gender, and geographic area between African American and Caucasian women has not been explored (Kumanyika et al., 2014; Johnston et al., 2011; Rosenbaum et al., 2017; State of Obesity, 2018). Also, African Americans are mostly underrepresented in weight loss studies (Kumanyika et al., 2014; Rosenbaum et al., 2017) making such research necessary.

Lifestyle modification is a plausible behavioral change that could influence obesity incidence and prevalence. According to Fussman (2015), 35.5% of individuals living in Detroit did not perform leisure time activities, and only 17.9% performed adequate physical activities. About 40.8% and 33.3% consumed less than one fruit and one vegetable serving per day, respectively (Fussman, 2015). Only 15.8% consumed fruits and vegetables more than five times per day (Fussman, 2015, Kim et al., 2018). Based on the multifactorial plausible factors known to cause obesity, research can conclude that many factors influence the high incidence and prevalence of obesity in any given environment, including income inequality (Kim et al., 2018). As such, Kim et al. (2018) suggested that future studies should assess the effects of potential area-level factors, such as an individual's residence status (rental and ownership status) on obesity.

Purpose of the Study

Due to the disproportional pattern by which obesity affects subpopulation groups (Rosenbaum et al., 2017), the unequivocal manner by which the burden of obesity and its comorbidities persist among different ethnic and racial groups, and the epidemic trends of the condition, obesity has become a serious public health concern. Therefore, in this study, a cross-sectional design was used to conduct a quantitative evaluation of selected secondary data from the 2016 BRFSS questionnaire to determine the association between an area-level factor and obesity in African American and Caucasian women in Michigan. The purpose of this study was to investigate the association between obesity, the dependent variable (DV), and an area-level factor such as an individual's residence status documented in the 2016 BRFSS using questions such as "Do you own or rent a home?" The residence status is the independent variable (IV) in this study. The findings of this study could facilitate public health efforts in promoting effective programs tailored to address the unique needs of priority populations to improve and sustain quality health outcomes (Kim et al., 2018). This study is essential because obesity is a known risk factor to multiple chronic health outcomes (Hales, Carroll, Fryar, & Ogden, 2017; Kim et al., 2018). The increase in obesity among certain racial groups has been documented and reported by many researchers. According to Zenk, Mentz, Schulz, Johnson-Lawrence, and Gaines (2017), there has been an increase in BMI among African American and Hispanic women living in lower-income areas. Whether the specified area-level factor under investigation in this study plays a role in the increase of BMI among African Americans and Hispanics is unknown. However, if such an association is found, it may play a crucial role in public health intervention in reducing obesity prevalence and incidence. As stated by Kim et al. (2018), substantial reduction of obesity triggered risk factors or an area-level factor or environment determinant could lower the health burden associated with obesity among vulnerable populations.

Research Questions and Hypothesis

RQ1: What is the association between the area-level factor residential status (own or rent), and obesity risk among adult African American women after controlling for income, education, and age?

$H_0$1: There is no association between the area-level factor residential status (own or rent) and obesity risk among adult African American women after controlling for income, education, and age.

H_a1: There is an association between the area-level factor residential status (own or rent) and obesity risk among adult African American women after controlling for income, education, and age.

RQ2: What is the association between the area-level factor residential status (own or rent) and obesity risk between adult African American and Caucasian women after controlling for income, education, and age?

$H_0$2: There is no association between the area-level factor residential status (own or rent) and obesity risk between adult African American and Caucasian women after controlling for income, education, and age.

H_a2: There is an association between the area-level factor residential status (own or rent) and obesity risk between adult African American and Caucasian women after controlling for income, education, and age.

Theoretical Framework

I used two theories to guide my research to help explain the association between an area level factor (rent or own) and obesity in African American and Caucasian women in Michigan. The first theory was social cognitive theory (SCT) and the second was social ecological model (SEM). Although both theories are used as a foundational guide, SCT was the primary focus because the cultural perception of weight among certain groups has been shown to influence weight and weight outcomes (Joseph, Keller, Ainsworth, Hooker, & Mathis, 2017). According to Joseph et al. (2017), behavioral capability, outcome expectations, self-efficacy, self-regulation, and social support systems of SCT can be used to guide a culturally appropriate physical activity intervention against obesity among African American women. Culture is relevant because it plays an essential role in African Americans' perception of a healthy weight concept within a household or at the individual level (Joseph et al., 2017).

Social Cognitive Theory

SCT was incorporated to support and explain relational variables and the significance of this study. The goal was to frame the purposes and use of the research findings to effectively guide obesity prevention and reduction in public health efforts. In other words, findings from this study could be used to frame public health interventions and health promotion measures for reduction and prevention of obesity and could lead to a decrease in the prevalence and incidence of obesity among African American women in Michigan. The findings from this study may also influence environmental and public housing policies that undermine the health status of African American women in Michigan. Study findings could also inform policymakers on the role or effects of housing tenure on obesity. Similarly, obesity-related morbidity and mortality cases could potentially be reduced and new and innovative approaches on how to address public health issues relating to obesity prevention and research for future research could be considered.

Individual behavior is a risk factor for obesity (Glanz, Rimer, & Viswanath, 2015). Glanz et al. (2015) posited that behavior is influenced by cognition (self-efficacy, outcome expectations, and knowledge) in accordance with social processes that inform action such as behavior change. The major constructs of SCT involve cognitive, social, physical, and environmental factors that influence behavior (Glanz et al., 2015). For example, self-efficacy defines an individual's ability to employ self-determination (confidence) to ensure their capability and ability (such as behavior/personality) to perform a task that produces an outcome. To relate self-efficacy in the context of obesity, an individual or group of individuals (community) must believe in their ability to self-acquire skill sets to conduct or perform an act (e.g., physical activity) focused at reducing or preventing weight gain. Collective efficacy is another construct of SCT and used in explaining or determining group (community) or (target population) confidence or ability to perform actions that result in desired outcomes (Glanz et al., 2015). Outcome expectations explain what (outcome) is desired from performing an action (Glanz et al., 2015). Knowledge is another key construct of the SCT and employed to influence behavior and cognition to inform action such as a behavior change.

Glanz et al. (2015) further described the environmental constructs of SCT in terms of observational learning or the ability to inform, learn, and conduct behavior through the observation of others; normative beliefs, which depict the role of culture on health-seeking behavior; and social recognition, experienced or expected from performing an action, and social support, which defines the level of support perceived from one's social peers (community, network, church groups, etc.). Although normative belief and culture are not variables included in this study, researchers have shown that these constructs or determinants influence inclination toward physical activity (Perrin, Caren, Skinner, Odulana, & Perrin, 2016). Overall, physical inactivity is an important risk factor for obesity (Perrin et al., 2016).

Glanz et al. (2015) also described barriers and opportunities as part of the constructs of SCT. Barriers and opportunities define perceived attributes of the sociophysical environment that may improve or diminish the ability to perform a behavior. For example, the lack of parks and recreation centers or healthy grocery stores in high-density African American neighborhoods, coupled with other negative aspects of the built environment, such as high crime or violence, may deter outdoor activities and increase the risk of obesity in certain population groups (Piontak et al., 2017).

Another rationale for choosing SCT to guide this study's questions, hypotheses, and purpose is that SCT addresses the multifactorial determinants (behavior and lifestyle choices, race or ethnicity, gender, biology, socioeconomic conditions, environment, etc.) associated with obesity. Another reason for selecting SCT is that some existing literature shows SCT's efficacy in guiding obesity interventions and health promotion efforts. For example, interventions guided by SCT to improve self-efficacy on appropriate nutrition intake and family support have been shown to be effective toward buying and eating healthier foods in adults (Anderson, Winett, & Wojcik, 2007).

Social Ecological Model

In this study, SEM was used to explain the association between area-level factors, such as residence ownership or rental status, and obesity risk among African American and Caucasian women. McLeroy, Bibeau, Steckler, and Glanz (1988) developed SEM from Bronfenbrenner's ecology theory. SEM can be used to guide and explain sociodemographic factors and health outcomes or behaviors at many levels of interpersonal, intrapersonal, and environmental factors (McLeroy et al., 1988; McLaren & Hawe, 2005).

Researchers have applied SEM in numerous studies for evaluation of health outcomes, behaviors, and risk factors (Novilla, Barnes, Natalie, Williams, & Rogers, 2006; Kothari, Edwards, Yanicki, & Hansen-Ketchum, 2007; Raneri & Wiemann, 2007; Vantamay, 2009). SEM has been used to explain smoking cessation and tobacco control (Kothari et al., 2007). It has been used to explain community-based health interventions and promotion measures as well (McLeroy, Norton, Kegler, Burdine, & Sumaya, 2003).

The interpersonal level construct describes social factors (Glanz et al., 2015; McLeroy et al., 2003). For instance, an area-level factor such as residence status (own or rent status) presents different opportunities or challenges for an individual or family within the socioenvironmental context. Access to walking paths, fresh produce stores, and community parks may be limited depending on the residence status and environment. Such limitations could affect inclination toward an obesity lifestyle or behavior. SEM constructs, such as interpersonal, intrapersonal, and environmental or community factors, are represented in this study as the area level factor (residence status: own or rent) was evaluated. In other words, women's residence status (ownership or rental status) was explained using three SEM constructs (interpersonal, intrapersonal, and environmental or community constructs). Similarly, the effects of confounders (income, education, and age) on obesity was explained using interpersonal, intrapersonal, and environmental or community factors as well. The intrapersonal constructs will explain effects of age, income, and education on obesity. Environment or community and interpersonal level will explain the effects of residence status (own or rent) on obesity risk among selected women.

Nature of the Study

In this study, I used a cross-sectional design, which allows for assessment of risk relationships, including prevalence and incidence between variables (Creswell & Creswell, 2017). A quantitative research method was used in this study as well, which provides a foundation for testing theories and quantifying variables objectively (Creswell & Creswell, 2017). A quantitative method allows for application of a postpositivist ideology into a research design (Creswell & Creswell, 2017). With a post-positivist perspective, a research inquiry is deterministic and not based on perceived knowledge common to qualitative research (Creswell & Creswell, 2017; Wilkins & Woodgate, 2008). The application of a cross-sectional design and quantitative research method in this study allowed the need to account for confounders or covariate (Creswell & Creswell, 2017). The quantitative inquiry was evaluated using secondary data collected from the 2016 BRFSS survey. In this study, a cross-sectional design is implicated in default because the 2016 BRFSS data were collected using a cross-sectional approach.

The research questions and hypotheses contain the DV or outcome variable, which in this study is obesity. Obesity was operationalized as a nominal variable, the obese group and the not obese group. The IV is the area level factor. The area level factor in question is residence status, grouped into either own status or rent status; it is a nominal variable. Income, education, and age are three confounders/covariates that was accounted for in the study. The inclusion criteria was African American and Caucasian women age 18 and older who live in Michigan. Based on the 2016 BRFSS secondary data, the women included are randomly selected and not randomly assigned. For the exclusion criteria, homeless women were excluded from the study. Women with familial history of obesity will also be excluded to avoid and limit spurious errors or distortion of the findings where study outcomes could be wrongfully influenced by family history, if not excluded rather than attributed to residence status (own or rent status). Walden Institutional Review Board (IRB) approval was obtained before the 2016 BRFSS secondary data were analyzed. Only deidentified data were analyzed and published. Once the data are obtained or downloaded, they were stored in a password-protected and secured computer.

Both obesity and area-level factor (residence status) are nominal variables. A nominal variable fits the assumption of binary logistic regression (Statistics Solutions, 2016). The statistical analysis was performed in two parts: the descriptive and inferential analyses. The descriptive analysis was conducted using tables and charts appropriate based on the variable's level of measurement. For the inferential analysis, binary logistic regression was used to address the two research questions. For both the descriptive and inferential statistical analyses, the Statistical Package for the Social Sciences (SPSS) software was used.

For sample size estimation, the G*Power software was used to calculate the required minimum sample size. For the sample size estimation, predetermined effect size value for the calculation was set at 2.0. The beta value for the Type II error was set at 20% (0.20) and the corresponding statistical power value was set at 80% (0.80). The predetermined alpha value for the estimation of Type I error was set at 5% (0.05) while the corresponding confidence level was set at 95% (0.95).

Definitions

Allostatic load: Cumulative physiologic stress due to chronic socioeconomic disadvantage (Tan, Mamun, Kitzman, Mandapati, & Dodgen, 2017) and an agglomerative physiological dysregulation indicative of cardiovascular events and all-cause mortality (Tomfohr, Pung, & Dimsdale, 2016).

Area level factor: An environmental construct that influences the health status of individuals within a given community (Cook, Tseng, Tam & Lui, 2017).

BMI: An obesity indicator calculated using weight in kilograms (kg) divided by height (m^2) and rounded up in the nearest 0.1 kg/m^2 (Centers for Disease Control and Prevention [CDC], 2017).

Community: A group of persons defined by their geographical location, population density, heterogeneity, size, physicality, or the types of social organizations or technological influences present or by their formal and informal interactions (Minkler, 2012). A community can also be a group of people sharing commonalities such as race, ethnicity, sexual orientation, occupation, and political interest (Minkler, 2012).

Cross-sectional design: A type of observational study in which a sample of persons from a population are enrolled into a survey to capture self-reported information about their exposures and health outcomes for specific metrics (Creswell & Creswell, 2017). A cross-sectional study can be used to assess the prevalence, incidence, and risk of health outcomes or exposure or risk factors at a given time period (Creswell & Creswell, 2017; CDC, n.d.).

Dependent variable (DV): The outcome variable whose variability depends on the manipulation of the IV or predictor variable (Edmonds & Kennedy, 2016).

Empirical evaluations: A process to classify the degree to which a specific program or policy empirically fulfills or does not address a standard or norm.

Empirical statements: A descriptive about what is the case in the real world rather than what ought to be the case and can be numerically explained using numerical terms and empirical evaluations (Cohen, 1980).

External validity: The extent to which the study results, outcomes, or findings can be applied (generalized) to similar settings or relevant or similar groups (Edmonds & Kennedy, 2016).

Housing tenure: The total number of owners occupied or rented dwellings within a given community (Badland et al., 2017).

Hypothesis: A provisional explanation that accounts for a set of facts that can be verified through further investigation (Sukamolson, 2007).

Independent variable (IV): The variable controlled or manipulated by the researcher to assess its effect on the DV (Edmonds & Kennedy, 2016).

Internal validity: The extent to which the results of a study are due to the IV and not by the influence of other plausible or alternative factors (Edmonds & Kennedy, 2016).

Obesity: An abnormal storage of fat reserves that limits activity and decreases longevity, i.e., lifespan (Pardina et al., 2018). Obesity is also a disequilibrium between energy consumed (intake) and energy expenditure (González-Muniesa et al., 2017). BMI category for obesity is ≥ 30.0 kg/m^2 (Tsai, Lv Xiao, & Ma, 2016; World Health Organization, n.d.).

Obesogenic environment: A living condition containing a high number of characteristics that facilitate obesity (i.e., more caloric intake and less energy expenditure) and fewer resources that promote a healthy weight (Bell, Kerr, & Young, 2019).

Overweight: An excess body adiposity quantified using the BMI (Arroyo-Johnson & Mincey, 2016). BMI category for overweight is between the range of 25.0–29.9 kg/m^2.

Prevalence: A measure of how often or how frequent a disease or condition occurs in a society (Creswell & Creswell, 2017). Prevalence is calculated by dividing the number of people who have the disease or condition by the total number of people in the group (Healthy People, 2020).

Quantitative study: A social research method that employs or uses an empirical approach and empirical statements (Cohen, 1980). Creswell (1994) defined quantitative research as an approach used to explain a phenomenon via numerical data collection and analysis employing mathematically based methods.

Social determinants of health: Factors (variables) that influence the environments in which people live, learn, work, play, worship, age, and are born (Arroyo-Johnson & Mincey, 2016). Such influences affect a wide range of health status, functions, and quality-of-life outcomes and risks (Arroyo-Johnson & Mincey, 2016).

Socioeconomic status (SES): An individual's social standing (position) based on educational attainment, employment level, income, and perceived poverty status (Pathirana, & Jackson, 2018).

Structural racism: The macro level systems, social forces, institutions, ideologies, and processes that interact with one another to generate and reinforce inequalities among racial and ethnic groups (Gee & Ford, 2011).

Variable: A factor or characteristics from the data collected that a researcher wants to analyze (Sukamolson, 2007). For example, the variables of interest for the unit of analysis or sample in this study implicated in the 2016 BRFSS are obesity status, area level factor (rent or own), age, gender, education, and income.

Assumptions

First, I assumed that SCT and SEM were appropriate theoretical foundations for my study. This is an assumption because other theories, such as the health belief model (HBM), have been used to address health interventions, including obesity. For example, Rezapour, Mostafavi, and Khalkhali (2016) applied HBM constructs in a physical education program to increase physical activity and reduce obesity. However, I did not choose HBM for this study because HBM constructs (perceived susceptibility, perceived severity, perceived benefits, self-efficacy, and barriers to performing an action or a behavior, cues to action) are focused more on individual abilities not group or environmental factors (Glanz et al., 2015). In other words, HBM is used to examine why people do not act to prevent, detect, or control health conditions at the individual level (Glanz et al., 2015). In contrast, the focus of this study is on group-based community level assessment. Thus, the ecological based theories, such as SCT, guide intervention at a population level (Glanz et al., 2015). Also, I chose SCT and SEM because they have the interpersonal and environmental constructs.

Second, I assumed that a cross-sectional study design was enough to evaluate my DV and IV within the context of my target population because the 2016 BRFSS data set was collected in the same manner. However, it is possible that self-reported information may not align with clinical data; unfortunately, there is no clinical data to validate the information reported by the participants via a self-reported survey. Third, I assumed that a binary logistic regression was the best appropriate statistical analysis to investigate the association between study variables.

Scope and Delimitations

The total combined sample size of the 2-year (2014–2016) MiBRFSS data set intended for use in this study is 28,899 interviews, both from the landline and cellphone calls. Data demographics for race were as follows: 23,405 non-Hispanic White; 2,996 non-Hispanic Black; 468 non-Hispanic Asian or other Pacific Islander; 234 non-Hispanic American Indian/Alaska Native; 731 non-Hispanic other/multi-racial; 387 non-Hispanic Arab; and 678 Hispanic. Those with unknown race/ethnicity were not included. The use of combined 2 years' data will allow the opportunity for generating enough statistical power for this study. Sampling, collection, and weighting methods were consistent for the period being studied.

With a cross-sectional survey there are inherent threats to the internal and external validity. These limitations were described in Chapter 3. Different types of limitations are common with secondary data-driven cross-sectional studies because certain aspects of the data sets cannot be manipulated, restructured, and redesigned (Creswell & Creswell, 2017). For example, if a variable was originally sampled as a nominal variable, that variable can never be converted to an ordinal, interval, or ratio level (Creswell & Creswell, 2017). Different types of biases also exist in a cross-sectional research design that could create a Type I or Type II error and thus distort the findings of the study (Creswell & Creswell, 2017). Some examples are selection, mortality, testing, instrumentation, recall, interview, and researcher biases (Creswell & Creswell, 2017). For this reason, biases was considered and addressed in the study. For the 2016 MiBRFSS, the land line telephone numbers contacted for interview purposes were selected using a list-assisted protocol and random-digit-dialed methodology with a disproportionate stratification based on phone bank density that identifies whether the phone numbers were directory listed or not (BRFSS, 2016). Each year, the sample size of cell phone numbers was randomly selected from dedicated cellular telephone banks separated by area code and exchange within the state of Michigan (BRFSS, 2016).

Obesity is also influenced by behavioral risk factors, such as alcohol consumption, smoking status, and lack of leisure time physical activity. Even when these risk factors were included in the original 2016 MiBRFSS data set, they are not part of the test variables in this study. The environmental variable—rent or own—was part of the data set, which for this study is the IV, while obesity is the DV and is included in the 2016 MiBRFSS.

The theoretical framework used in this study was SCT and SEM. Both SCT and SEM are explanatory, coherent, and reliable constructs and aligned with the study variables and purpose. SCT has also been used to evaluate health outcomes. Even when SCT and SEM were appropriate and relevant in describing and explaining the study intent, rationale, and logic, the study findings cannot be explained or generalization of the conclusion be applied beyond the target population described in this study. Also, no causal relationship could be drawn from the findings of this study; rather, a correlational relationship can be made because there is no experimental verification of the spatiotemporal assessment of the exposure (predictor variable) outcome sequence established in the study prior to the data collection or analysis of the data set.

Limitations

The use of 2016 MiBRFSS secondary data does not allow for fundamental change in the data set because the BRFSS data set was collected as surveillance data and not unique to this study. Therefore, certain conditions that could have been controlled during the data collection process were no longer feasible. For example, the need to sample a higher number of other racial groups to make the sample selection proportionate would no longer be possible. The data set showed that more Caucasians (23,405) were included in the 2016 MiBRFSS than all the other races combined (5,494).

A cross-sectional research design lacks a spatiotemporal sequence between the exposure of interest (residence ownership or rental status) and obesity status. In other words, there was no information included in the survey to verify whether the participants owned or rent their residence before they became obese or whether they were obese prior to renting or owning their residence. Based on the limitations specified, the study can only be used to infer a correlational association and not a causal relationship because the research design was not experimental or quasi-experimental. Also, the study findings cannot be generalized beyond the study participants included in the study because the sample size was not representative of the larger population of the target location of interest. The correlational inference is limited to participants used in the study and may not apply to individuals not included in the MiBRFSS.

In addition, the 2016 BRFSS health and demographic information obtained from the participants was not collected through a clinical diagnosis provided by a medical practitioner but rather via participants' self-reported interview approach. As such, recall and misclassification biases were likely to occur. Also, the BRFSS database was primarily established for surveillance purposes; therefore, the information provided by the participants may not match their clinical diagnosis. Fluctuation relating to place may also occur because people move around or lose their residence due to unforeseen circumstances; as such, residence status can fluctuate between renting and owning and even geographical locations.

Significance

The purpose of this study aligned with Michigan's public health goals and campaign efforts to improve the overall health outcomes among residents. For example, Michigan's

Nutrition, Physical Activity, and Obesity (MiNPAO) program aims to prevent, control, and delay obesity through promotion of healthy eating, physical activity, and healthy social determinants of health. Findings from this study could be used to guide and inform MiNPAO activities, planning, and program implementation to derive meaningful outcomes specifically on obesity and related health burdens. In addition, positive findings from this study may add additional evidence-based information to strengthen the goals of MiNPAO program efforts on obesity prevention.

Additional information identified or emerged from this study will inform and enhance new ideas on public health and medical practices. If positive correlation exists, it will encourage health practitioners or public health professionals to identify priority areas in need of preventive measures necessary to address the burden of obesity. With more evidence-based findings, public health agencies could establish community health linkages and action-based plans specific to the area-level factors to address obesity measures. Partnership with specific stakeholders invested in obesity health issues could be influential in promoting rigorous efforts in exploring other possible correlated obesity determinants that may be linked to the area-level factor in question to address the short-term, intermediate, and long-term effects of such factors. Developing or modifying health strategies within the community and institutional practice specifically on obesity interventions and programs to influence individual and policy level decisions about the need of affordable evidence-based obesity programs are warranted.

Promotion of positive social change ideation is a multidirectional approach and may involve system thinking, social dynamic reflexivity, collaborative efforts, advocacy, political engagement, and ethical considerations (Laureate, 2015). For example, the study findings could influence change at the individual- and policy-level by demonstrating the link between the area-level factor under investigation and obesity, specifically among African American women in

Michigan. Such findings may increase obesity awareness among the target population. Through effective obesity prevention, advocacy, and community engagement, stakeholders could be actively empowered to build capacity and outreach efforts within the target communities to support members of that community to seek and maintain healthy lifestyle choices. The focus on African American women as the primary target population in this study could help highlight the needs regarding culturally sensitive public health intervention approaches and policies that could promote obesity awareness and reduce the structural barriers to improve lifestyle programs in impoverished areas.

Summary

This study was a quantitative cross-sectional study of secondary data from the 2016 MiBRFSS. The IV was the area-level factor of home ownership (rent or own), which may also be inferred to as housing tenure within the study context or literature review. The DV was obesity, and the confounders (controlled for the study) were age, income, and education. The study design was cross-sectional. This design is consistent with evaluating the presence or absence of an association between variable using statistical analysis such as binary logistic regression. A cross-sectional design was employed as a default because the 2016 BRFSS data were collected using a cross-sectional design (BRFSS, 2016). The study sample included adult African American and Caucasian females ages 18 years and older. The study excluded homeless women and women with a history of familial obesity from both races. For sample size estimation, the G*Power software was used to calculate the required minimum effective sample size. In Chapter 2, I discuss SEM and SCT and the rationale for choosing these theories. I also explain why the constructs of these theories can be used to understand how an area-level factor (rent or own) can influence the outcome variable (obesity). Chapter 2 also contains the literature review.

Chapter 2: Literature Review

Introduction

Obesity is a chronic incapacitating condition of multiple origin (etiology) and continues to be a public health threat of epidemic proportions in the United States (Seidell, & Halberstadt, 2016) and worldwide. Individual (intrapersonal) behavior, community (interpersonal), environmental (area level), policy, gender, race, and genealogy (pedigree) are all factors that influence obesity and its etiology. Obesity is associated with health behaviors and health outcomes such as T2D, hypertension, certain types of cancer (Arroyo-Johnson & Mincey, 2016) and even all-cause mortality (National Heart, Lung, and Blood Institute, 2013). According to Arroyo-Johnson and Mincey (2016) risk factors for obesity are energy imbalance between nutrition and physical activity (i.e., between consumption and expenditure), direct and indirect genetic effects, gene-environment interactions, and social determinants of health. In this chapter, literature pertaining to these aspects was discussed to provide some understanding of obesity and its multifactorial etiologies.

Obesity burden exists for people of all races, ethnicities, age groups, gender, and socioeconomic statuses in the United States (Ogden, Carroll, Fryar, & Flegal, 2015). For example, the CDC estimated that the yearly medical costs of obesity in the United States were $147 billion in 2008; individual medical costs for people who have obesity were $1,429 higher than those of people who were not obese (Finkelstein, Trogdon, Cohen, & Dietz, (2009). Financial burden is not the only detrimental effect associated with obesity. Death from obesity and its related comorbidities is high in the United States. Obesity has been linked to cardiovascular disease or heart disease, and heart disease is the leading cause of death for both males and females in the United States (CDC, 2017).

In Detroit, Michigan, the number of persons living with obesity is higher than in many other cities in the state (Koh et al., 2017). Obesity prevalence is higher in the city of Detroit and its surrounding suburbs (Koh et al., 2017; Koh et al., 2015; State of Obesity, 2018). According to 2013–2015 BRFSS data, 30–35% of obese adults were reported in Michigan (Fussman, 2015). Currently, Michigan ranks 16th on obesity burden (31.2%) among all 50 states (State of Obesity, 2018). In 2015, about 35.1% of adults ages 45–64 years were obese in Michigan (Fussman, 2015). In 2016, according to BRFSS data, 32.5% of adults in Michigan were obese with BMI ≥ 30, and 35% were overweight (BMI 25–29.9; Fussman, 2015; State of Obesity, 2018). In Michigan, roughly 37.6% of African Americans are obese (Fussman, 2015; Johnston et al., 2011; State of Obesity, 2018). Although the multifactorial etiology of obesity has been widely studied, a comparative assessment of obesity risks based on income level, nutrition, physical activity, education level, employment status, age, gender, and geographic area between African American and Caucasian women has not been explored (Johnston et al., 2011; Kumanyika et al., 2014; Rosenbaum et al., 2017; State of Obesity, 2018). Also, African Americans are underrepresented in weight loss studies (Kumanyika et al., 2014; Rosenbaum et al., 2017), making this research study necessary for the community.

Lifestyle modification is a plausible behavioral change that could influence obesity incidence and prevalence. According to Fussman (2015), 35.5% of individuals living in Detroit, Michigan, did not perform leisure time activities and only 17.9% performed adequate activities (Fussman, 2015). About 40.8% and 33.3 % consumed less than one fruit and one vegetable serving per day, respectively (Fussman, 2015). Only 15.8% consumed fruits and vegetables more than five times per day (Fussman, 2015; Kim et al., 2018). In addition to the multifactorial plausible factors known to cause obesity, many other factors influence the high incidence and prevalence of obesity in any given environment, including income inequality. Kimet et al. (2018) suggested that future studies should assess the effects of potential area-level factors, such as an individual's residence status (own vs. rent) on obesity (Kim et al., 2018).

The following literature review indicates the lack in knowledge (or limited current knowledge) of what is known about area-level factors (homeownership: rent or own) and their association with obesity. In this literature review, the area-level factor and obesity in the United States and elsewhere was examined. I also reiterate the chronicity, complexities, comorbidities, and outcomes of obesity within my study population.

The purpose of this study was to investigate the association between obesity and the area-level factor of an individual's residence status (own vs. rent). This study's findings could help public health efforts to promote effective programs tailored to address the unique needs of the target population to improve sustainability of health outcomes (Kim et al., 2018). This study is essential because obesity is a known risk factor to multiple chronic health outcomes (Kim et al., 2018). For instance, Zenk et al. (2017) suggested that an increase in BMI occurs among African American and Hispanic women living in lower-income areas. Whether the specified area-level factor under investigation in this study plays a role in the increase of BMI among African Americans and Hispanics is unknown. If any association exists in this study, substantial reduction of such a risk factor or an area-level factor or environmental determinant linked to obesity could lower the health burden associated with obesity among the vulnerable target population (Kim et al., 2018).

In Chapter 2, I detail the literature research strategy, describe SCT and SEM (theoretical foundations), present any recent studies that used SCT and SEM in obesity-related public health endeavors, and describe investigations on obesity and area-level factors. Because of the multifactorial complexities of obesity etiologies and because obesity etiologies are outside the scope of study for this research, I do not emphasize such literature in this review. The literature review will also contain recent obesity studies using a cross-sectional design. Within the epidemiology section, I state obesity prevalence among adult African American and Caucasian women in Michigan; I state obesity-related mortality and obesity-related comorbidities. I also state any risk factors for obesity categorized as social, behavioral, and environmental. For example, social risk factors may include variables that influence obesity, such as level of education attained, income, and level of employment. Behavioral risk factors may include the extent of physical activity conducted, while environmental risk factors may include the primary area level factor (rent or own, housing tenure etc.) and other subfactors such as presence or absence of parks and recreation centers. Chapter 2 concludes with a summary of the important points or findings from the literature review.

Theoretical Foundation

SEM provides constructs that can be used to explain the relationship between a persons' interaction with their physical and sociocultural environment (Stokols, 1992). According to Glanz et al. (2015), SEM incorporates multilevel factors (socioenvironmental, personal, and policy) to explain behavior and outcome. In context, obesity is a chronic condition influenced by interpersonal, intrapersonal, policy, and environmental factors. Therefore, it was logical to employ SEM and SCT for this study. SEM and SCT are two theories with fundamental ecological constructs that focus on intrinsic and extrinsic factors to guide the research inquiry. The use of SEM and SCT in this study formed a comprehensive approach to inform the research, frame the hypothesis, and develop a complete understanding of the intrinsic and extrinsic links between the area-level factor (rent or own) and obesity risk among African American and Caucasian women in Michigan.

As stated previously, SEM was developed from Bronfenbrenner's ecology theory. The pioneers of SEM were McLeroy et al. (1988). SEM has been previously used in several studies to explain sociodemographic factors and health outcomes or behaviors at different levels of interpersonal and intrapersonal (intrinsic factors) and environmental determinants (extrinsic factors; McLaren & Hawe, 2005; McLeroy et al., 1988). SEM has also been applied in numerous public health program evaluations of health outcomes, behaviors, and risk factors or exposures (Kothari et al., 2007; Novilla et al., 2006; Raneri & Wiemann, 2007; Vantamay, 2009). SEM has been used to explain smoking cessation and tobacco control (Kothari et al., 2007) and community-based health interventions or promotion measures (McLeroy et al., 2003).

The interpersonal construct can be used to describe social or cultural factors and education attainment achieved (Glanz et al., 2015; McLeroy et al., 2003). Intrapersonal construct can be used to describe intrinsic factors such as age, obesity status, genetic composition, sex, gender and gender role, marriage status, and familial history of health outcomes or behavior (Glanz et al., 2015; McLeroy et al., 2003). Environmental determinant construct can be used to describe and explain external cues such as social determinants of health, area-level factors, and built environment that influences health and behavior (Glanz et al., 2015; McLeroy et al., 2003). Interpersonal, intrapersonal, and environmental or community factors represented in this study are area level factor (residence status: own or rent status), obesity, age, gender, income, and education. Application of SEM and SCT will guide the current study to allow for improved implementation of obesity policies, and public health intervention measures on obesity that can facilitate a positive social change environmental in terms of informing us about the impacts of housing tenure on obesity status (Golden, McLeroy, Green, Earp & Liberman, 2015).

SCT is a derivative of the ecological theory called the social learning theory (SLT) developed by Albert Bandura in 1977 (Wulfert, 2018). According to Wulfert (2018), the key elements of Bandura's SLT theory include declination of the humanist and existentialist view. A humanistic view is an inclination or acceptance that human behaviors are regulated by the environment (Bandura, 1977, 1986). It also suggests that external determinants of behavior such as rewards, punishments, and internal determinants (inherent to one's self) such as thoughts, expectations, motivation, and beliefs, emerges from a system of other participating determinants that influence behavior (Bandura, 1977 & 1986). It has been suggested that via self-regulatory processes, humans can control their actions, or manipulate behavior by setting goals, arranging environmental inducements, generating cognitive strategies, evaluating goal attainment, and taking responsibility for their actions (Bandura, 1977 &1986). Bandura's SLT was later augmented to the SCT in 1986. The new augmentation emphasized the roles of cognition, self-regulation, self-efficacy, outcome expectations, motivation, and observational learning in changing behavior (Wulfert, 2018). Based on the facts stated above, it was logical to include the SCT as one of the theories for this study.

According to Glanz et al. (2015), behavior is influenced by cognition. Collective efficacy is a construct identified in SCT. It is used to determine individual or group confidence for the ability to perform actions to achieve the desired outcomes (Glanz et al., 2015). Outcome expectations can be used to explain an outcome expected from performing a given action (Glanz et al., 2015). Knowledge, another SCT operational construct is used to explain behavior and it is influenced by cognition which informs self-efficacy and outcome expectations (Glanz et al., 2015).

Table 1 showed the comparison between SEM and SCT versus HBM and TTM. It is important to note that the HBM and TTM will not be used as the theoretical foundation for this study. However, it is important to compare competing theories such HBM and TTM to the SEM and SCT intended to use in this study to provide a better understanding and justification to why SEM and SCT were selected over HBM and TTM.

Table 1

Key Differences and Strengths Between SEM and SCT Versus TTM and HBM

SEM	SCT	HBM	TTM
Strengths	Incorporates, individual, group, cognitive, environmental, culture, and normative beliefs; Assesses intention and goal setting behavior; Incorporates role of social support in promoting health behavior; Allows building behavioral capacity; and Action oriented	Constructs are intuitive and easily defined. When included in an intervention, self-efficacy construct is an effective tool in defining behavior change. Individual focus.	Uses efficacy and impact to monitor outcomes.
Weaknesses	May overlook environmental influence on behavior; Constructs analysis is limited; and Needs reliable and valid measurement criteria.	Variability in measurement of constructs; Lack of adequate reliability and validity testing measures; Lacks scientific rigor; Lacks specificity in defining relationship between constructs; Self-efficacy constructs not clearly defined; and Cues to action construct not clearly defined.	Stages are not well defined. Not well applied to diverse cultures; Does not clearly define the stage at which intentional behavior begins; and Not well known how the stage phase predicts behavior.

Literature Search Strategy

For Chapter 2 literature synthesis, I reviewed U.S. based and global studies related to obesity risk factors, obesity and its relationship to environmental factors, obesity and weight gain, obesity comorbidities, disparities in the distribution of obesity amongst African American and Caucasian, obesity and home ownership, obesity and area level factors, obesity and income, obesity among adult African American and Caucasian women and I also, reviewed studies pertaining to the global prevalence of obesity. Since current literature investigating the role of area level factors (rent or own) and its influence on obesity among African American or Caucasian women living in Michigan is nonexistent or is limited, I expanded my search to include relatable studies performed between, 2015 and 2019. This range does not define my scope of search because valuable studies outside this scope may have been mentioned within my work to describe the theories use (SCT and SEM) or to the fill the gap lacking in current literature on my topic. However, articles older than 5 years were included only if relevant and implicated the SCT and SEM. Also, articles older than 5 years with detailed and relevant information on the current methodology intended to use in this study were not excluded.

I also used the Walden electronic library databases to refine my literature search and selection. Other databases used for literature search are: Academic Search Complete, Science Direct, CINAHL Plus, and Springer Science + Business Media. Public databases such as BioMed Central, PubMed from the National Center for Biotechnology Information (NCBI), and Google Scholar. I also utilized internet searches to review statistical data and obesity chronic disease factsheets from the World Health Organization, the CDC and the national health and nutritional examination survey (NHANES). My study data is retrievable from the MiBRFSS.

The search terms used to select relevant literature for this study are *obesity and African American women, obesity and Caucasian women, area level factors and obesity, obesity and income, obesity and socioeconomic status, obesity and Michigan, rent tenure and obesity, obesity comorbidities, obesity and weight gain, obesity and inequities in health, obesity and physical* *environment, obesity and homeownership, obesity and neighborhood status, obesity and residential status, obesity and ethnic groups, weight gain and as a precursor for obesity, obesity and body mass index, overweight and housing tenure, obesity and health outcomes, obesity and health disparities, obesity and socioeconomic disadvantage, obesity and the United States,* and *global obesity epidemic*.

The article selections were based on their relevance to the current research inquiry. Since this is a quantitative study, most qualitative articles identified were excluded from the literature review process. All selected articles were peer-reviewed journals and were all electronic files. Also, all selected articles reviewed were written in English language.

Literature Review Relevant to Research Questions/Hypotheses

Obesity and Area-Level Factors

Area-level factors such as built environment have been linked to obesity, however, the impact of these factors on obesity is still not extensively examined with enhanced instruments (Cook, Tseng, Tam, & Lui, 2017). Cook et al. (2017) used the area-level disadvantage index to address some of the area level factor-triggered outcome. Area level disadvantage index is an instrument designed to facilitate better understanding of the association between area-level factors and obesity (Cook et al., 2017). Area-level disadvantage index consist of five unfavorable SES variables associated with proportion of an individual intrinsic determinants for persons aged 25 years or older who did not have a four-year college degree; males aged 16 years or older who were unemployed; persons with incomes below the federal poverty level; households that receive public assistance, and female-headed households (Cook et al., 2017). These indicators have been used in prior research to assess neighborhood disadvantages (Barber, Hickson, Kawachi, Subramanian, & Earls, 2016; Desmond & Kubrin, 2009; Sampson, Sharkey, & Raudenbush, 2008), as such, applicable in obesity studies.

Using univariate, bivariate, and multiple logistic regression analyses to evaluate the association between demographic characteristics and obesity among selected target population, (Cook et al., 2017) showed income, age, and education has some influence on obesity area-level factors. The sample population consisted of 1525 Asian American adolescents ages 12-17 years old. The 2007–2012 California Health Interview Survey (CHIS) was the source of the data used in the study (Cook et al., 2017). Age, gender, nativity, individual-level SES (income and education), and two lifestyle variables (fast food consumption and physical activity) were accounted (Cook et al., 2017). The primary target population for the study is Asian Americans, overall, the key differences in SES between dissimilar ethnic groups and neighborhood disadvantages were highlighted and was shown to influence obesity status among priority populations (Cook et al., 2017). The justification and need for the current study that seek to address the disadvantageous area level factor (own a home or rent status) among African American on its impact on obesity outcome was also supported and rationalized by Cook et al. (2017).

Certain neighborhood characteristics have been shown to influence obesity as living conditions are not static but rather continuum (Sheehan, Cantu, Powers, Margerison-Zilko, & Cubbin, 2017). In other words, some area level confounders including an influx of individuals of a more diverse ethnic background, growth or increased poverty, urbanization, gentrification, ‘white flight’ etc., may influence chronic condition such as obesity (Sheehan et al., 2017). Contextually, housing ownership or renting status is also a neighborhood characteristic.

Similarly, such area level determinant is also part of the microcosm of social determinant of health.

Sheehan, Cantu, Powers, Margerison-Zilko, & Cubbin (2017) used a quantitative method with a cross-sectional study design to investigate the relationship between area level factors and obesity between two groups of people with different socioeconomic standings. They used 2,339 women ages 21-57 years old for the study (Sheehan et al., 2017). Poverty was an obesogenic variable accounted for in the study (Sheehan et al., 2017). A multivariate analysis was conducted using a secondary data source from the 2012-2013 Geographic Research on Wellbeing (Sheehan et al., 2017). Data relating to neighborhood characteristics were retrieved from a latent class growth model conducted on census tracts (Sheehan et al., 2017). The authors concluded that living in areas (census tracts) with consistent high poverty levels was more aligned with being obese versus areas with lower poverty indexes.

Housing is a key social and environmental determinant of health, it affects individuals and communities in several ways (Braubach, 2011). Housing tenure has been demonstrated to affect a person's health outcomes (Braubach, 2011). Also, a bidirectional relationship exists between housing affordability and health outcomes (Baker, Mason, Bentley, & Mallett, 2014). These researchers investigated the relationship between homeownership (rent or own) and a health outcome, but none implicated obesity in African American or Caucasian women living in the United States (Baker et al., 2014; Braubach, 2011).

A cross sectional study conducted by Tranter and Donoghue (2017) showed that obesity is high amongst persons living in public housing, renters, or persons who maintain a mortgage versus people who completely own their homes. Tranter and Donohue (2017) used a bivariate cross-tabulations and regression to analyze the 2011 Australian Survey of Social Attitude

(AuSSA) secondary data. AuSSA is a large national sample of Australian adults aged 18 and older (Tranter & Donoghue, 2017). The inquiry addressed by Tranter & Donoghue (2017) in their study is similar and relevant to the current study which seeks to identify the association between obesity and home ownership and renting status. Tranter & Donoghue (2017) also emphasized the differences in food consumption patterns between people who rent, own a home or pay a mortgage accounted for the observed differences in BMI, with mortgagees more likely to be obese than those that own their homes (Tranter & Donoghue, 2017). They also concluded that further research is needed to identify the role of housing tenure such as renting and ownership on obesity. The gap identified or proposed by Tranter & Donoghue (2017) aligned well with premise of this study, which seeks to evaluate the impacts of house renting or ownership on obesity in African American and Caucasian women living in Michigan.

According to Tranter and Donoghue (2017), the inherent limitations of the 2011 AuSSA survey secondary data set were transferred into their findings. For example, they emphasized that the overweight and obese status recorded in the 2011 AuSSA data set were overestimated and underestimated respectively (Tranter & Donoghue, 2017). As a result, they concluded that their sampling may have been biased because older adults and people with lower level of education were less likely to respond to mailed surveys, population who were also likely to have higher BMI measurements (Tranter & Donoghue, 2017). Also, the study reiterates that, the use of a cross-sectional design does not suggest a causal inference between variables of interest. (Tranter & Donoghue, 2017).

Hales, Fryar, Carroll, Freedman, Aoki, & Ogden (2018) employed a serial cross-sectional design to assess the height and weight of adults ages 20 years or older. The data source for the study was the 2001-2016 NHANES, a nationally representative survey of the civilian, noninstitutionalized US population (Hales et al., 2018). Cofounders accounted for the study included age, ethnic origin, gender, and level of organization. The primary outcome investigated was obesity (BMI $\geq$ 30) and severe obesity (BMI $\geq$40) (Hales et al., 2018).

Obesity prevalence differs between metropolis and even within ethnicities (Hales et al., 2018). Hales et al. (2018) suggested that the prevalence of obesity and severe obesity is higher in persons living in non-metropolitan areas compared to metropolitan areas (Hales et al., 2018). They also emphasized that obesity is higher in non-Hispanic African American women compared to non-Hispanic Caucasian (Hales et al., 2018). In the study, urbanization is an environmental component, but it was not defined in terms of owning or renting a house (Hales et al., 2018).

Homeownership is directly and indirectly beneficial for health (Dietz & Haurin, 2003; Rohe & Stewart, 1996; Rohe, Van Zandt, & McCarthy, 2002; Rossi & Weber, 1996). Unfortunately, very few researchers examine the direct effects of homeownership to obesity (Dietz & Haurin, 2003; Rohe & Stewart, 1996; Rohe et al., 2002; Rossi & Weber, 1996). Direct effects of homeowners included sense of control and security, residential stability, and social integration versus renters (Dietz & Haurin, 2003; Rohe & Stewart, 1996; Rohe et al., 2002; Rossi & Weber, 1996). However, some of the indirect effects of homeownership are social and economic benefits which included higher average housing quality (Friedman & Rosenbaum, 2004). Similarly, homeownership provides the foundation of accretion of wealth (Boehm & Schlottmann, 2008). For instance, according to the U.S. census bureau, 74% of Caucasian households own their homes, compared to only 45% of African American and Latino households (Census Bureau, 2013).

Finnigan (2014) used secondary data from the 2012 Current Population Survey (CPS) from the Integrated Public Use Microdata Series (IPUMS) for assessing the effects of homeownership and obesity. They used logistic regression for their statistical analysis age and household (HH) income were accounted in the study. They also suggested that disparities in health and non-health such as socioeconomic benefits through the process of homeownership exists between African American or other ethnic minorities and Caucasian (Finnigan, 2014). Finnigan (2014) also emphasized that homeownership is the fundamental socioeconomic resource for health. As such, Finnigan (2014) and other researchers' conclusions described in this manuscript supported the need for the premise of this study which aims to examine the association between house ownership or rental status and obesity.

In addition, Finnigan (2014) stated that health advantages of homeownership are unequivocally and disproportionately distributed between people of different ethnicities or races or within people of the same race or ethnicity. For instance, 'Caucasian homeowners are exceptionally healthier compared to Caucasian renters and renters from all other minority groups (Finnigan, 2014). Unlike Finnigan (2014) who utilized self-reported data to assess the effects of housing characteristics on obesity, Clair and Hughes (2019) employed a biomarker specific for stress and infection called C-Reactive Protein (CRP) to show that an association between housing characteristics and health outcomes exists. Clair and Hughes (2019) concluded that 'housing tenure type (rent or own), cost burden and desire to stay in current home are associated with CRP. The study was a longitudinal design and the use of CRP biomarker associated with infection and stress to explore the effects of area level factors is unique because it focuses on intrinsic or biological connection to environmental determinants. Housing information, demographic characteristics, and health behaviors were accounted for and the unit of analysis for the study were individuals living the United Kingdom. A hierarchical linear regression model was used to analyze CRP of individuals and all housing characteristics, across various age groups and ethnicities. They showed that private renters had significantly higher count of CRP or worse state of health than owners with a mortgage (Clair & Hughes, 2019). In other words, private renters had poorer health versus non-renters (homeowners) (Clair & Hughes, 2019). Clair and Hughes (2019) provided relevant basis for the current study because they showed that housing tenure can negatively affect general health, therefore it is warranted to further investigate the effects of housing tenure on obesity among and between specific ethnic and racial population.

Badland, Foster, Bentley, Higgs, Roberts, Pettit, and Giles-Corti, (2017) conducted a study and employed a multivariate multilevel logistic regression to compare exposure and health outcome measures. The analysis was adjusted for sex, age, employment status, and household income and composition. Badland et al. (2017) indicated that poor self-reported health, crime or incivilities, dissatisfaction with one's community were linked to minorities within low income groups who rent their homes versus those who own house. They emphasized that housing-type, quality, and affordability were also considered as an important area level socioeconomic determinant of health and are important in determining outcome measures for several health conditions (Badland et al., 2017). Both Baker et al. (2014) and Badland et al. (2017) provided foundation to support the rationale proposed in this study inquiry.

Drewnowski, Aggarwal, Cook, Stewart, and Moudon (2015) evaluated the association between residential property values such as owning or renting a home, and annual household income on diet quality among persons of various race and age groups. Diet quality was measured using the Healthy Eating Index (HEI). Using data set from the 2008-2009 Seattle Obesity Study

(SOS) with a population-based sample size of 1,116 adults from King County Drewnowski, Aggarwal, Cook, Stewart, & Moudon (2015) explored the association between area level factor and diet quality stated. The sociodemographic data were obtained via a 20-minute telephone survey (Drewnowski et al., 2015). Dietary data were obtained from food frequency questionnaires (FFQs; Drewnowski et al., 2015). Home addresses were geocoded to the tax parcel and residential property values were obtained from the King County tax assessor (Drewnowski et al., 2015). A multivariable regression analysis was used to evaluate the relationship between selected SES and diet quality measured (HEI scores; Drewnowski et al., 2015). They concluded that there is an association between HEI, income, education, and residential property values, especially among women (Drewnowski et al., 2015). As a result, they proposed that residential property values are predictor of socioeconomic disparities of health status, education, and income (Drewnowski et al., 2015).

Obesity Epidemiology Comorbidities

Obesity is a known risk factor for heart disease (Mandviwala, Khalid, & Deswal, 2016). Obesity adversely effects cardiovascular functions by facilitating progression of atherosclerosis. It also promotes ventricular remodeling and is a risk factor to stroke, myocardial infarction (MI), and heart failure (Kachur, Lavie, Milani, & Ventura, 2017). According to the CDC, one in four (25%) or 610,000 people die of heart disease in the U.S. annually (Kachur et al., 2017). Heart disease is the number one cause of death in both men and women in the U.S. (Kachur et al., 2017). Obesity is also a precursor to accumulation of high amount of low-density lipoprotein (LDL), and low amount of high-density lipoprotein (HDL), commonly known as the bad and good cholesterol respectively (Kachur et al., 2017). Hence, obesity and LDL predispose a person to heart disease regardless of race or gender (Kachur et al., 2017). Obesity is also a risk factor lead to high blood pressure (HBP) or hypertension, and diabetes (CDC, n.d.). Similarly, HBP and T2D are common risk factors of CVD (Mandviwala et al., 2016).

Obesity is defined or categorized by BMI (Tomfohr, Pung, & Dimsdale, 2016). The BMI is also one of the components used to measure allostatic load (Tomfohr et al., 2016). Allostatic load is an indicator of cardiovascular event (Tomfohr et al., 2016). Other risk factors associated with allostatic load are waist circumference, HDL, total cholesterol and HDL ratio, triglycerides, glycosylated hemoglobin A1C (HbA1c), systolic blood pressure, diastolic blood pressure, and salivary cortisol (Tomfohr et al., 2016).

Several housing related determinants has been shown to influence obesity (Baker et al., 2014; Braubach, 2011; Clair & Hughes, 2019; Tranter & Donohue, 2017). Several housing related determinants also influences allostatic load (Baker et al., 2014; Braubach, 2011; Clair & Hughes, 2019; Tranter & Donohue, 2017). According to Tan, Mamun, Kitzman, Mandapati, & Dodgen (2017), the percentage of renter occupied houses (a negative factor) within a given geographical spatial arrangement (neighborhood) and households living in poverty are significantly associated with high prevalence of obesity and obesity related illnesses in African American women. Also, individuals living in households receiving public assistance, with transport barriers, overcrowded, and those with low level of education has high risk of obesity and related chronic diseases (Tan et al., 2017). Similarly, non–military unemployed persons aged 16 years or older, and non-male headed households has high prevalence of obesity and obesity related illnesses especially among African American women (Tan et al., 2017). They also concluded that low-income status and neighborhood disadvantageous factors, independently and synergistically affect allostatic load and that education and health behaviors mediate the relationship.

Tan et al. (2017) using a cross-sectional design demonstrated the effects of neighborhood and individual factors on allostatic load described above using 220 African American women at risk of obesity-related diseases (Tan et al., 2017). The women were selected from the Better Me Within Program (Tan et al., 2017). The mean age and its standard deviation were 50.1 and 11.2 years respectively. Similarly, the mean BMI and its standard deviation was 36.7 and 8.4 kg/m^2 respectively (Tan et al., 2017).

In Michigan, Acker et al., (2002) identify several variables contributing to obesity in African American women. Some of the factors include but are not limited to geographic, environmental, and living conditions. In Michigan, 95% of African American population is concentrated in 12 counties while 55% alone live in Detroit (Acker et al., 2002). Detroit does not have safe and affordable parks, well-lit streets, recreational centers, etc., for recreational physical activities (Acker et al., 2002) Living in urban areas such as Detroit has been shown to restrict access to available healthy food choices (Acker et al., 2002). Therefore, as noted earlier by several researchers, poor living and environmental conditions promotes inclination to physical inactivity among African American women in Detroit thus facilitating the increase in the prevalence of obesity (Acker et al., 2002).

Globally, Arnold et al. (2015). suggested that about 481,000 (3.6%) of all new cancer cases in adults, ages 30 years and older were attributable to high BMI in 2012. According to CDC (2017), the risk factors of certain types of cancers and obesity were found among overweight women while obesity has been demonstrated to increases the risk for breast, colorectal, esophageal, uterine, pancreas, and kidney cancers (CDC, 2017). CDC indicated that by just excluding breast and colorectal cancers, the incidence of weight-related cancers is still predicted to increase 30% to 40% by 2020 (CDC, 2017). According to CDC (2017) report on cancer and obesity, over 600,000 people in the U.S. were diagnosed with overweight and obesity triggered cancers in 2014(CDC, 2017). Of this diagnosis, approximately two in three adults 50-74-years-old had cancers (CDC, 2017). About 55% was diagnosed in women and 24% in men. Non-Hispanic African American and non-Hispanic Caucasian had higher incidence rates cancers compared with other racial and ethnic groups (CDC, 2017). Also, the incidence of obesity-related cancers, except for colorectal cancer, increased by 7% between 2005 and 2014 (CDC, 2017). Obesity has been shown to be associated with 13 different types of cancers which includes meningioma, multiple myeloma, adenocarcinoma of the esophagus, cancers of the thyroid, postmenopausal breast, gallbladder, stomach, liver, pancreas, kidney, ovaries, uterus, colon and rectum (colorectal).

Bandera et al. (2016) used a population-based, case control study design to examine the burden of obesity. Obesity as a carcinogenic risk factor of the ovary maybe more prominent in post-menopausal stage among African American women (Bandera et al., 2016). Bandera et al. (2016) reiterated that obesity and extreme adult weight gain could increase the risk of ovarian cancer in African American women after menopause. For their statistical analysis, Bandera et al. (2016) used a multivariate logistic regression to analyze the associations between weight gain and cancers. Adults with BMI greater than 25kg/m^2 were included in the study analysis for the assessment of the risk of ovarian cancer which included a population sample of 512 cases and 722 controls (Bandera et al., 2016). The data set used was retrieved from the African American Cancer Epidemiology Study [AACES] (Bandera et al., 2016).

In a prospective cohort study conducted with 24,000 African American and 14,064 Caucasian adults ages 40-79 years old (Conway et al., 2018) showed that the risk of diabetes incidence is higher as BMI increased. Also, diabetes incidence was 2-fold higher among African American than Caucasian for individuals with normal BMI (Conway et al., 2018). Conway et al.

(2018) employed Pearson's chi-square analysis of variance (ANOVA), logistic regression models, and Kruskal-Wallis tests to evaluate incident diabetes between African American and Caucasian.

Risk Factors of Obesity: Social, Behavioral and Environmental

Social risk factors: Age, income, level of education, race. Income, education, and age are confounders that was accounted for in this study. In Ogden et al. (2017) conducted to assess the relationship between income and obesity, they accounted for race, education, and age in their analysis. The data used was produced by NHANES (Ogden et al., 2017). Participants' income was grouped into four federal poverty level (FPL): ≤130%, >130% to ≤350%, and >350% (Ogden et al., 2017). Persons' education level was grouped into high school graduate or lower, some college, and college graduate (Ogden et al., 2017).

With age-adjusted samples Ogden et al. (2017) demonstrated that the prevalence of adult obesity was lower (31.2%) among individuals under the highest income group (≥350 FPL) than other groups; 40.8% for those with >130% to ≤350% FPL and 39.0% for individuals with ≤130% FPL (Ogden et al., 2017). The age-adjusted prevalence of obesity among college graduates was lower (27.8%) than among those with some college (40.6%) and those who were high school graduates or less (40.0%; Ogden et al., 2017). In this study, there were substantial differences in obesity trends based on sex and racial/Hispanic subgroups (Ogden et al., 2017).

In the Ogden et al. (2017) study, the obesity prevalence among women was lower (29.7%) in the highest income group compared to 42.9% in individuals with middle income and 45.2% among the group with the lowest income (Ogden et al., 2017). In the study, then assessment of the trend of obesity included non-Hispanic Caucasian, non-Hispanic Asian, and Hispanic women, which only showed significant difference in Caucasian women. No difference in obesity prevalence among individuals under different income groups was observed in non-Hispanic African American women (Ogden et al., 2017). Overall, they concluded that obesity prevalence decreased with increased levels of income and educational attainment among women (Ogden et al., 2017).

Behavioral Risk Factors: Physical Inactivity and Diet

Physical activity and diet are behavioral factors that may directly or indirectly influence obesity (Makambi & Adams-Campbell, 2018). Physical inactivity and poor diet have been shown to increase the risk for weight gain and obesity. In a case-controlled study Makambi and Adams-Campbell (2018), examined the associations between socio-demographic factors such as age, marital status, income, and education and obesity after accounting physical activity, dietary supplements, nutrients, and smoking or alcohol consumption among African American women. Anthropometric measurements such as BMI, intake of dietary supplements, nutrients, socio-demographic factors (age, marital status, income, and education) and physical activity (time spent on activities such as running, swimming, paying basketball, etc.) were measured. Data was collected from 197 African American women ages 55 years and older (Makambi & Adams-Campbell, 2018). They concluded that for each one level increase in education level, obesity decreased by about 7% based on vigorous physical activity performed (Makambi & Adams-Campbell, 2018). Age also showed a significant positive but indirect influence on obesity through vigorous physical activity because obesity levels increased by approximately 6% for each additional year gained in age (Makambi & Adams-Campbell, 2018). They concluded that conducting vigorous physical activity mediates the association between education and age on obesity (Makambi & Adams-Campbell, 2018).

Using a path analysis, Makambi and Adams-Campbell (2018) could predict the causal sequence of events between IVs or exogenous determinants such as sociodemographic factors, intermediate variables, and outcome or endogenous determinants such as physical activity, nutrients, dietary supplements, smoking, alcohol, and obesity (Makambi & Adams-Campbell, 2018). They recommended the use of path analysis for this type of study because it increases our understanding of direct and indirect effects of IVs on DVs. They also suggested that small sample produced low statistical power (Makambi & Adams-Campbell, 2018). According to the authors, the use of self-report data can produce biases (Makambi & Adams-Campbell, 2018).

Mason et al. (2016), examined the effects of a mindfulness-based intervention (MBI) on eating, sweets consumption, and fasting glucose levels in obese adults. The participants were drawn from the SHINE randomized controlled trial in attempt to reduce weight gain, long-term. One hundred and ninety-four obese individuals were enrolled in the study (Mason et al., 2016). Participants' median age and BMI was 47.0 ± 12.7 years and 35.5 ± 3.6, respectively (Mason et al., 2016). The participants composed of 78 % women and was subjected to a 5.5-month diet-exercise program with or without mindfulness training and stress reduction (Mason et al., 2016). Participants who were included in the study are those with BMI between 30 and 45.9, abdominal obesity (waist circumference > 102 cm for men and > 88 cm for women, individuals aged 18 years or older (Mason et al., 2016). Participants with Type1 and Type 2 diabetes (fasting glucose ≥ 126); pregnancy; breastfeeding or fewer than 6 months post-partum; corticosteroid and/or immune-suppressing or immune-modulating medications, prescription weight-loss medications; untreated hypothyroidism; history of coronary artery disease; and those with history of active bulimia were excluded (Mason et al., 2016). Of 194 participants enrolled in the trial, 156 (80.4 %) completed the 6-month assessment, and 149 (76.8 %) completed the 12-month assessment

(Mason et al., 2016). Participants were primarily Caucasian women with average age of 47.0 ± 12.7 years and mean BMI of 35.5 ± 3.6 kg/m^2 (Mason et al., 2016).

Every study participant attended a 2-2.5 hour; 12 weekly evening sessions, 3 biweekly sessions, and one session 4 weeks later, plus an all-day weekend session [5.0 hours for the active control group, 6.5 hours for the Mindfulness Based Intervention (MBI) group (Mason et al., 2016). All sessions were led by a registered dietitian in the active control and co-led by a registered dietitian and an MBI instructor in the MBI group (Mason et al., 2016). In the MBI group, eating techniques and flexible, self-directed caloric reduction, and increases in activity level, as taught in the Mindfulness Based Eating Awareness Training (MB-EAT) Program was encouraged (Mason et al., 2016). Mindfulness based stress reduction techniques (MBSRT) based on the MB-EAT Program such as body scan meditation, self-acceptance, and loving kindness meditation, mindful yoga, and mindful sitting meditation, was also taught in the MBI group (Mason et al., 2016).

Diet and exercise requirements were comparable between both groups, the MBI and active control groups (Mason et al., 2016). For diet requirements, participants were asked to adhere to modest calorie reduction (Mason et al., 2016). They were also instructed to reduce food intake of their choice by 500 calories, calorie-dense, nutrient-poor foods, and to increase the consumption of fresh fruits and vegetables, healthy oils, and proteins intake (Mason et al., 2016). For exercise, participants were instructed to increase their daily exercise regimen and to conduct structured aerobic and anaerobic exercise, such as bicycling, swimming, strength training, and walking (Mason et al., 2016).

Fasting blood glucose measurements was taken at every assessment (Mason et al., 2016). Participants' height was used to estimate the BMI (Mason et al., 2016). For details on how percentage of calories from sweet foods and desserts (sweets) and Mindful eating evaluations were calculated please refer to the study. The analysis of covariance (ANCOVA) was used assess the changes in eating of sweets and fasting glucose from baseline within 6 months and 12-months (Mason et al., 2016). Also, multiple regression was used to assess the relationship between increased mindful eating, reduced sweets intake and fasting blood glucose for participants in the MBI and active control groups (Mason et al., 2016). Mediation analysis was also used to assess the effects of self-reported mindful eating on assignment of fasting glucose and eating of sweets at each outcome assessment (Mason et al., 2016).

They concluded that for both groups, the association between 6-month changes in mindful eating and fasting glucose were statistically significant ($\beta = -0.18$, $p = 0.015$) even after adjusting for 6-month change in BMI (Mason et al., 2016). Also, changes in BMI at the 6-month mark significantly predicted changes in fasting glucose where greater reductions in BMI were associated with greater reductions in fasting glucose [$\beta = 0.18$, $p = 0.019$] (Mason et al., 2016). In the mindfulness group, the association between 6-month changes in mindful eating and fasting glucose was statistically significant ($\beta = -0.21$, $p = 0.038$) also even after adjusting for change in BMI (Mason et al., 2016). In the MBI group, a 6-month change in BMI was statistically significant in predicting changes in fasting glucose with greater reductions in BMI being associated with greater reductions in fasting glucose ($\beta = 0.22$, $p = 0.029$) (Mason et al., 2016). Therefore, they concluded that including mindful eating components into standard diet-exercise weight management programs may promote long-term stabilization of reduction of sweets consumption and maintenance of fasting glucose levels in obese adults without diabetes (Mason et al., 2016). The findings of this study are relevant because they advanced new ideas such as diet and exercise and other factors like mindfulness eating behavior that can mediate weight gain and obesity similar to the current study inquiry under investigation.

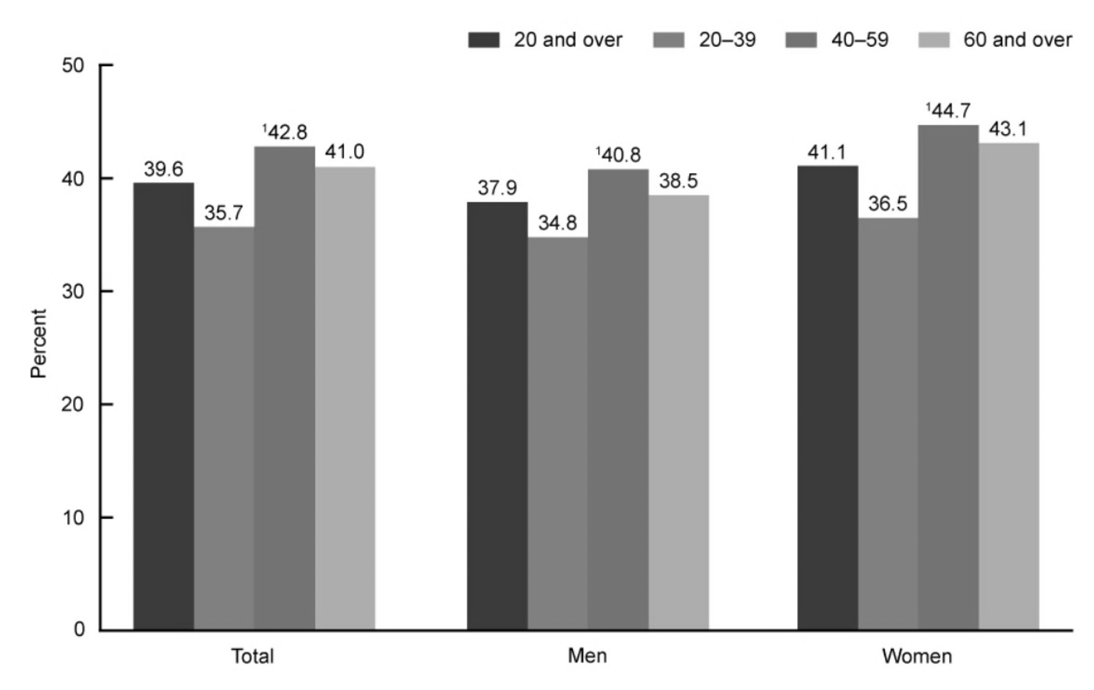
Obesity and Race

Racial differences in obesity outcomes exists (Powell, Jesdale, & Lemon, 2016). Race is an important factor to discuss since in this study African American women was compared to Caucasian women (Powell et al., 2016). Additionally, race linkage to obesity especially among African Americans has been demonstrated (Powell et al., 2016). Racism has been associated with obesity in African American, therefore, the internalization and or over consciousness (vigilance) of race and its discriminatory effects by African American, may also be associated to obesity (Powell et al., 2016). In the study, the reaction to race module was used to analyze over 12000 eligible African American participants responses to the race-related vigilance question generated from the 2002–2010 BFRSS data. The BRFSS question that addressed this concern was stated as follows: "*how often to you think about race*"? (Powell et al., 2016). The authors showed via multiple logistic regression that frequently thinking about race was associated with an increased risk for obesity (Powell et al., 2016).

The concentration of fast food restaurants or lack of healthy food options within a neighborhood or individual level behavioral characteristics such as the ability or inability to conduct physical activity within a deprived built environment is a key determinant of obesity (Bell et al., 2019). Bell et al. (2019) used a linear and Poisson regression analysis to evaluate the effects of structural racism on obesity (Bell et al., 2019). They concluded that race-driven inequality in homeownership and inequality in unemployment were associated with high obesity rates, in counties with >9% African American residents (Bell et al., 2019). A greater prevalence of obesity in counties displaying inequity in race, poverty, employment, and homeownership is suggests that social and environmental contexts predicts the risk of obesogenic (Bell et al., 2019).

Obesity and Prevalence

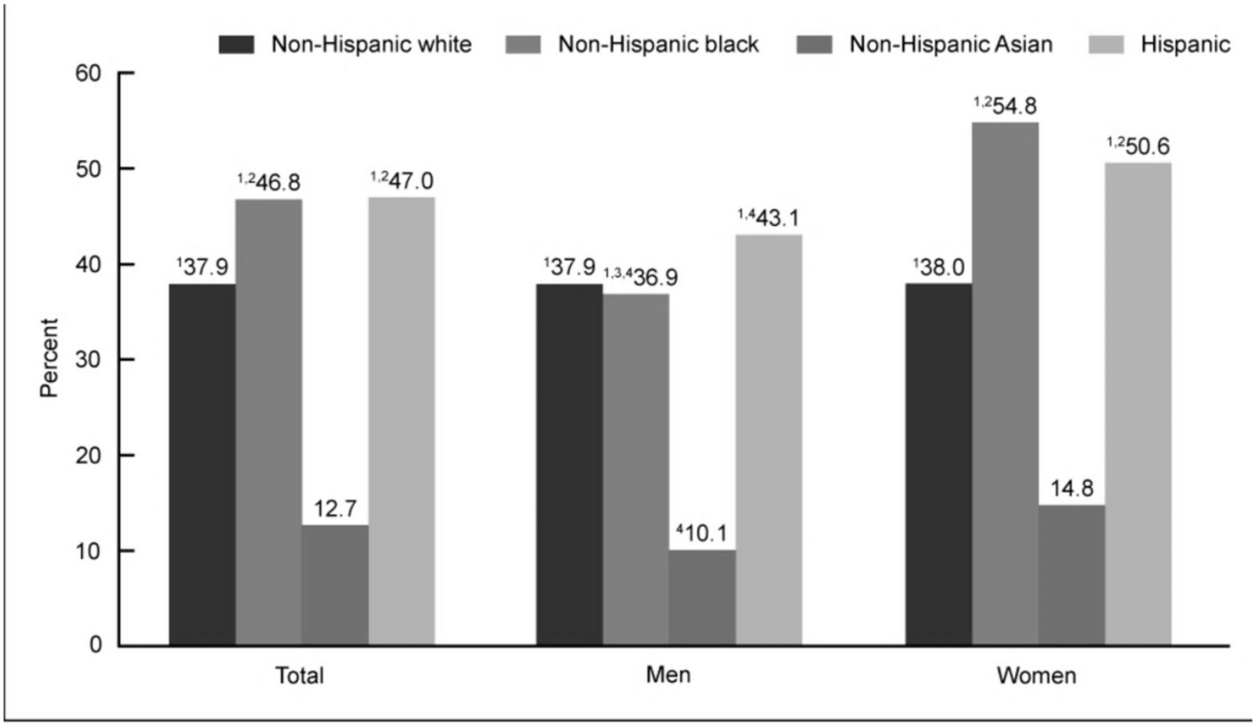
Obesity remains a challenge for public health and a risk factor for numerous comorbid diseases and death (Seidell & Halberstadt, 2016; National Heart, Lung, and Blood Institute, 2013). Therefore, research efforts targeting areas of obesity-related evidence-based interventions or knowledge is continuum ad warranted at all levels. According to NHANES, the prevalence of obesity in the United States between 2015–2016 is very high and comparable to the 2013–2014 rate (Hales et al., 2017). In 2015–2016, the prevalence of obesity was 39.8% in adults and 18.5% in youth (Hales et al., 2017). The prevalence of obesity (42.8%) was higher among middle-aged adults than among younger adults (35.7%; Hales et al., 2017). The overall obesity prevalence was higher among non-Hispanic African American and Hispanic adults versus non-Hispanic Caucasian and non-Hispanic Asian adults (Figure 1; Hales et al., 2017). They also concluded that within the general adult population, the prevalence of obesity was 38.0% in non-Hispanic Caucasian and 54.8% in non-Hispanic African American (Hales et al., 2017). About 14.8% with obesity are non-Hispanic Asian, and 50.6% women are Hispanic (Figure 2; Hales et al., 2017). Based on this information alone, approximately 16.8% difference in obesity rates exists between non-Hispanic Caucasian and non-Hispanic African American women (Hales et al., 2017). This literature also supports the need to conduct this inquiry focused on the obesity and its association with an area level factor such as house renting or owning status.



Significantly different from those aged 20–39.
NOTES: Estimates for adults aged 20 and over were age adjusted by the direct method to the 2000 U.S. census population using the age groups 20–39, 40–59, and 60 and over. Crude estimates are 39.8% for total, 38.0% for men, and 41.5% for women. Access data table for Figure 1 at: https://www.cdc.gov/nchs/data/databriefs/db288_table.pdf#1.
SOURCE: NCHS, National Health and Nutrition Examination Survey, 2015–2016.

Figure 1. Prevalence of obesity among adults 20 and older by sex and age: United States 2015-2016.

(Source: //https://www.cdc.gov/nchs/products/databriefs/db288.htm)



[1]Significantly different from non-Hispanic Asian persons.
[2]Significantly different from non-Hispanic white persons.
[3]Significantly different from Hispanic persons.
[4]Significantly different from women of same race and Hispanic origin.
NOTES: All estimates are age adjusted by the direct method to the 2000 U.S. census population using the age groups 20–39, 40–59, and 60 and over. Access data table for Figure 2 at: https://www.cdc.gov/nchs/data/databriefs/db288_table.pdf#2.
SOURCE: NCHS, National Health and Nutrition Examination Survey, 2015–2016.

Figure 2. Adults' Age-adjusted prevalence of obesity based on ages 20 years and older, sex, race, and Hispanic origin.

Obesity in Special Populations

Disproportionately, obesity and its comorbidities affect people in different ethnicities, race, gender and even occupation (Breland et al., 2017). In a veteran's health administrative (VHA) study conducted among veterans, African American women, women with schizophrenia, younger individuals, Native Hawaiian/Other Pacific Islander, and American Indian/Alaska Natives were at high risk of obesity (Breland et al., 2017). These veterans benefit from a care plan intended to address obesity and reduce health disparities (Breland et al., 2017). The VHA study was a national cross-sectional inquiry consisting of over 5 million primary care patients (347,112 women and 4,567,096 men), across 140 veteran facilities in the US (Breland et al., 2017). The data used in this study was produced by the Women's Health Evaluation Initiative

(WHEI) master database of outpatient, inpatient, and community care records, and VHA vital signs for both women and men VHA patients (Breland et al., 2017). All veteran patients with at least one VHA primary care visit in 2014 fiscal year (FY2014) were included in the study (Breland et al., 2017). Of 98% patients BMI reported, 41% (44% for women and 41% men) was obese while the overweight prevalence was 37% (31% for women and 38% men; Breland et al., 2017). When the analysis was stratified by age and gender, obesity prevalence was higher among older than younger veterans. The age and gender stratification are as follows: Men and women ages 18-44 years old had 46% and 40% obese prevalence respectively (Breland et al., 2017). Men and women ages 45-64 years old had 48% and 49% obese prevalence respectively (Breland et al., 2017). Obesity prevalence also differed by race/ethnic and comorbidity groups, with high obesity values among African American women (51%), women with schizophrenia (56%), and women (68%) and men 56%) with diabetes (Breland et al., 2017).

Another subpopulation of people who suffer from obesity and its comorbidities more than any other groups are those with mental health disorders (Jantaratnotai, Mosikanon, Lee, & McIntyre, 2017). Using epidemiological studies and meta-analysis researchers have projected that a relationship (co-occurrence) exists between obesity and depression (Jantaratnotai et al., 2017). Other researchers have reported a bidirectional relationship between obesity and depression (Rajan & Menon, 2017). While others have concluded that obesity is related to social stigma and ostracization during the onset of depressive symptoms (Mooney & El-Sayed, 2016). In the past, researchers have linked depression and stress as conditions that increases the risk of obesity with 58% occurring in depressed persons (Luppino, de Wit et al., 2010).

In a double-blind randomized cross over trial by Kiecolt-Glaser et al. (2015), the role of daily stressors, past depression, and metabolic responses to high-fat meals was examined as a possible cause for obesity. They evaluated resting energy expenditure (REE), fat and carbohydrate oxidation, triglycerides, cortisol, insulin and glucose before and after two high-fat meals and past daily stressors (Kiecolt-Glaser et al., 2015). Daily stressor was evaluated using the Daily Inventory of Stressful Events (DISE) and major depressive disorder (MDD) history instruments via the administration of the structured clinical interview for DSM-IV (Kiecolt-Glaser et al., 2015). They also concluded that prior day stressors plus depression could alter the metabolism of high fat meals leading to weight gain and subsequently obesity (Kiecolt-Glaser et al., 2015).

Obesity and Culture

Physical inactivity is an obesity risk factor (Makambi & Adams-Campbell, 2018). The ability to perform physical activity affects the risk for obesity (Makambi & Adams-Campbell, 2018). Fitted built and safe environment is the needed to motivate physical activities at an individual and a community level. Existing research has shown that even when the built environmental conditions/constructs are conducive for performing physical activity, social or an individual's belief system or culture could be overarching barrier to beneficial adoption of any given lifestyle choice (Makambi & Adams-Campbell, 2018). Perrin, Caren, Skinner, Odulana, and Perrin (2017) in their study showed that built environments such as parks and recreation center, walkable paths etc., are linked to physical activities and obesity. Therefore, they concluded that even with favorable physical features on its own, it is not enough and stand-alone factors to induce inclination to participate in physical activity or adopt a physically active lifestyle (Perrin, Caren, Skinner, Odulana, & Perrin, 2017). They also suggested that residents must decide to use these features in health-promoting ways (Perrin et al., 2017). In other words, implying that social norms and culture influences aspects of the physical environment and physical activity behaviors (Perrin et al., 2017). The study was a systemic, geocoded, and culturally based observational design conducted in rural Lenoir County in North Carolina (Perrin et al., 2017). The obesity prevalence in this rural county was 34% with a total population size of approximately 59,000, of whom 23.7% of the population lives below the FPL (Perrin et al., 2017). The study population was also approximately 41% African Americans, 53% Caucasians, and with 6% of other minorities including Latinos (Perrin et al., 2017). Overall, this study is relevant to the current study because it highlighted physical environment as an obesity risk, complexity of obesity etiology, environmental factors as feasible determinants for conducting weight management interventions, and other non-environmental factors such as intrapersonal beliefs (inherent cultural and social factors) may influence action or inaction in the adoption process of physical activeness lifestyle (Perrin et al., 2017).

Summary and Conclusions

Obesity continues to exist in an epidemic proportion in the U.S. and worldwide and obesity is a growing public health problem (Seidell, & Halberstadt, 2016). In addition to the multifactorial plausible factors known to cause obesity, there are many other factors that influence the high incidence and prevalence of obesity in any given environment including income inequality (Cook et al., 2017). In many literatures I reviewed, housing was an important social and environmental determinant that affect public health and quality of life (Baker et al., 2014; Braubach, 2011). Other researchers indicated that a bidirectional relationship exists between housing affordability and health status (Baker et al., 2014). Scientific evidence supporting the use of diet to control weight and reduce obesity exists but have been demonstrated for weight loss in short-term and not long-term basis (Byrne et al., 2003; Mann et al., 2007). Several studies covering the obesity risk factors, comorbidities, and related-health outcomes were discussed in this section of the dissertation. The reviewed sets of literature were discussed based the study rationale and purpose, design, method, statistical approaches used to address the research inquiry and the conclusion and recommendations reached by the author(s). The literature review areas covered in this section of the dissertation provided the evidence-based and scholarly foundations to address the key areas of Chapter 3 including methodology and sampling approaches for this study.

Chapter 3: Research Method

Introduction

The disproportional pattern by which obesity affects subpopulation groups and the unequivocal way the burden of disease is observed in different ethnic and racial groups warranted this study. The research questions in this study were structured to assess risk of obesity outcome in the exposure to the area-level factor house rent versus own. Based on the research questions, a quantitative approach and cross-sectional design using secondary data from the MiBRFSS were used to determine the association between the specified area-level factor and obesity in African American and Caucasian women in Michigan. In Chapter 3, the research design is described, methodology including the target population, sampling and sampling procedures, and threats to validity associated with the study.

Study Design and Rationale

A cross-sectional design was used for this study. A cross-sectional design allows for assessment of the relationship between variables that addresses risk, prevalence, or incidence rate of given outcome or exposure (Creswell & Creswell, 2017). Cross-sectional designs are evidentially adequate in evaluating the association between an outcome measure and its risk factors within a population or subpopulation during a specified time frame (Levin, 2006). Cross-sectional designs are also time saving and inexpensive approaches (Levin, 2006).

A cross-sectional design on its own without the support of experimental design settings cannot be used to infer causality because it cannot be used to account spatiotemporal sequence of events between an exposure and outcome (Levin, 2006). As such, it is difficult using a cross-sectional design to determine whether the exposure occurred before the outcome and vice versa (Levin, 2006). In cross-sectional studies, both the exposure and outcome are determined simultaneously (Carlson & Morrison, 2009). In other words, although an association may exist between the IV (exposure) of interest and DV (outcome), there may be no direct plausible evidence that the exposure caused the outcome observed (Carlson & Morrison, 2009). For this reason, causality cannot be determined.

Figure 3 shows a diagram of a cross-sectional design structure that illustrates the sampling parameter derived from the entire population, sampling criteria between the exposed and unexposed group, related observed outcomes based on the exposure status, and the risk of the outcomes observed in either the exposed or unexposed group.

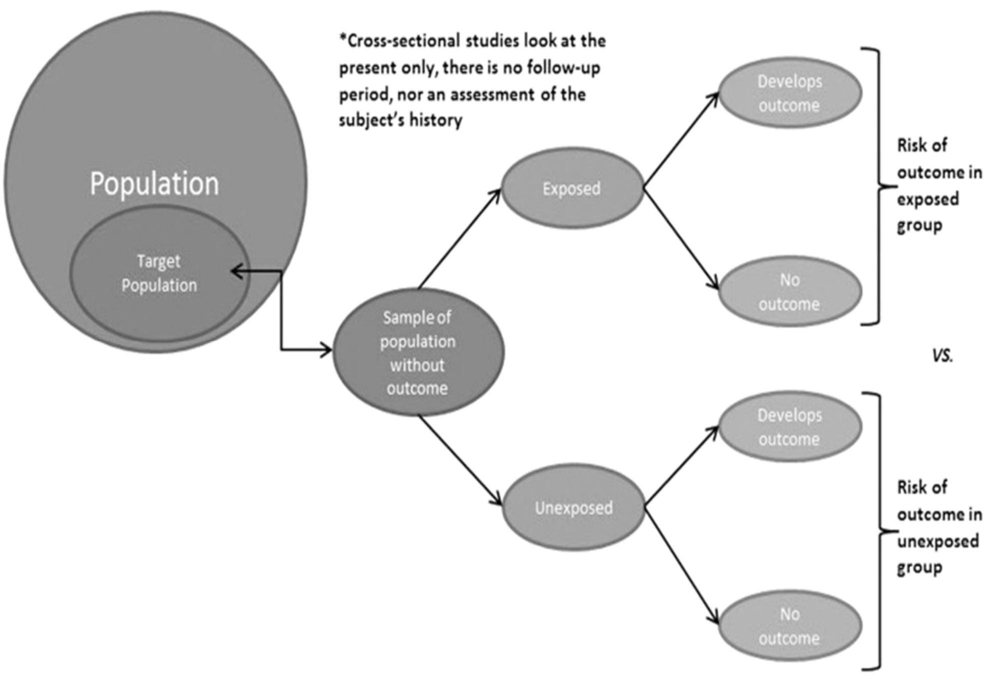


Figure 3. A cross–sectional design. Source: Nour and Plourde (2018)

An experimental or quasi-experimental design was used in this study because this research inquiry was not addressing an intervention or treatment or intended to draw a causal inference. According to Morrison and Carlson (2009), in an experimental design study, the exposed group is randomly selected and assigned preoutcome event occurrence. As such, an experimental design is primarily used to determine the efficacy of an intervention or treatment (Morrison & Carlson, 2009). Other designs, such as prospective or retrospective cohorts or case-control, were not considered for this study because they would not have fulfilled the time-sensitive delivery of the study findings. For example, with a prospective cohort, the exposed and unexposed are followed over a long period of time to determine the association between exposure and outcomes of interest (Morrison & Carlson, 2009). In a case-control approach, the outcome is determined and identified from the target population before the exposures associated with the outcomes are explored in detail and this design is time consuming.

As described earlier, a quantitative research method was used to address the study inquiry. A quantitative approach provides the basis from an objective perspective (Creswell & Creswell, 2017). A quantitative method also allows for the application of postpositivist perspectives (Creswell & Creswell, 2017). With a postpositivist perspective, a research inquiry is deterministic rather than subjective, commonly used in a qualitative study (Creswell & Creswell, 2017; Wilkins & Woodgate, 2008). The quantitative inquiry was evaluated using secondary data collected from 2014–2016 MiBRFSS surveys. The use of a cross-sectional design is the default approach because the 2014–2016 MiBRFSS data were collected using a cross-sectional design.

The 2014–2016 MiBRFSS data were previously collected for health indicators' surveillance purposes (BRFSS, 2016). In addition to being readily accessible, secondary data are advantageous because they provide access to large sample sizes (Carlson & Morrison, 2009). Similarly, an existing sample may cover a large geographic area and thus can be used to assess national trends of an exposure or outcome (Carlson & Morrison, 2009). Secondary data also have methodology disadvantages, including difficulty understanding how the original data were collected and data may not contain all the research variables of interest including the confounders and covariates intended by secondary users (Carlson & Morrison, 2009).

Study Variables

Each research question and hypothesis contain a DV or an outcome variable, which in this case was obesity. In this study, obesity was operationalized as a nominal variable: the obese group or the non-obese group. Similarly, each research question in this study contains an IV or a predictor variable, which in this case is the area-level factor. The area-level factor in question in this study is residence status, such as house ownership or renting. The residence ownership or renting status is a nominal variable. Income, education, and age were three confounders/covariates accounted for in the study. Education is grouped into three ordinal levels: (a) those who did not graduate from high school, (b) high school graduates, and (c) college graduates (BRFSS, 2016). Income was grouped into three ordinal levels: (a) those with annual income < $25,000 (low), (b) annual income $25,000 to $75,000 (middle), and (c) annual income ≥ $75,000 (high; BRFSS, 2016). Age was categorized into three ordinal variables: (a) ages 18–41 years, (b) 42–65 years, and (c) > 65 years (BRFSS, 2016).

Walden IRB approval was obtained before the secondary data were used, and only deidentified data were analyzed and published. Once the data were obtained, they were stored in a password-protected and secured computer. Because both obesity and the area-level factor (residence status) are nominal variables, the use of a binary logistic regression was appropriate for the analysis of the study variables (Statistics Solutions, 2016). The analysis was performed in two parts: descriptive analysis followed by inferential analysis. The descriptive analysis was conducted using appropriate tables and charts that aligned with the variable’s levels of measurement. To assess the inferential analysis piece in this study, a binary logistic regression was used to address the research questions and hypotheses. For both the descriptive and inferential statistical analyses, SPSS software was used.

For sample size estimation for a two-tail z-test analysis, the G*Power software was used to calculate the required minimum sample size. For the estimation of the study minimum sample size, the predetermined effect size value was 2.0. The beta value used for the Type II error was 20% (0.20), and the corresponding statistical power value was 80% (0.80). The predetermined alpha value used for the sample size estimation of Type I error was 5% (0.05), and the corresponding confidence level was 95% (0.95). After all the sample size estimation predetermination values were computed in the G*Power software, the minimum sample size generated for this study was 113 women participants to produce a result with an 80% statistical power. See Table 2 and Figure 4.

Table 2

*Sample Size G*Power Estimation*

Z tests – Logistic regression		
Options:	Large sample z-test, Demidenko (2007)	
Analysis:	A priori: Compute required sample size	
Input:	Tail(s)	= Two
	Odds ratio	= 2
	Pr (Y=1|X=1) H0	= 0.2
	α err prob.	= 0.05
	Power (1-β err prob.)	= 0.80
	R^2 other X	= 0
	X distribution	= Normal
	X parm μ	= 0
	X parm σ	= 1
Output:	Critical z	= 1.9599640
	Total sample size	= 113
	Actual power	= 0.8028456

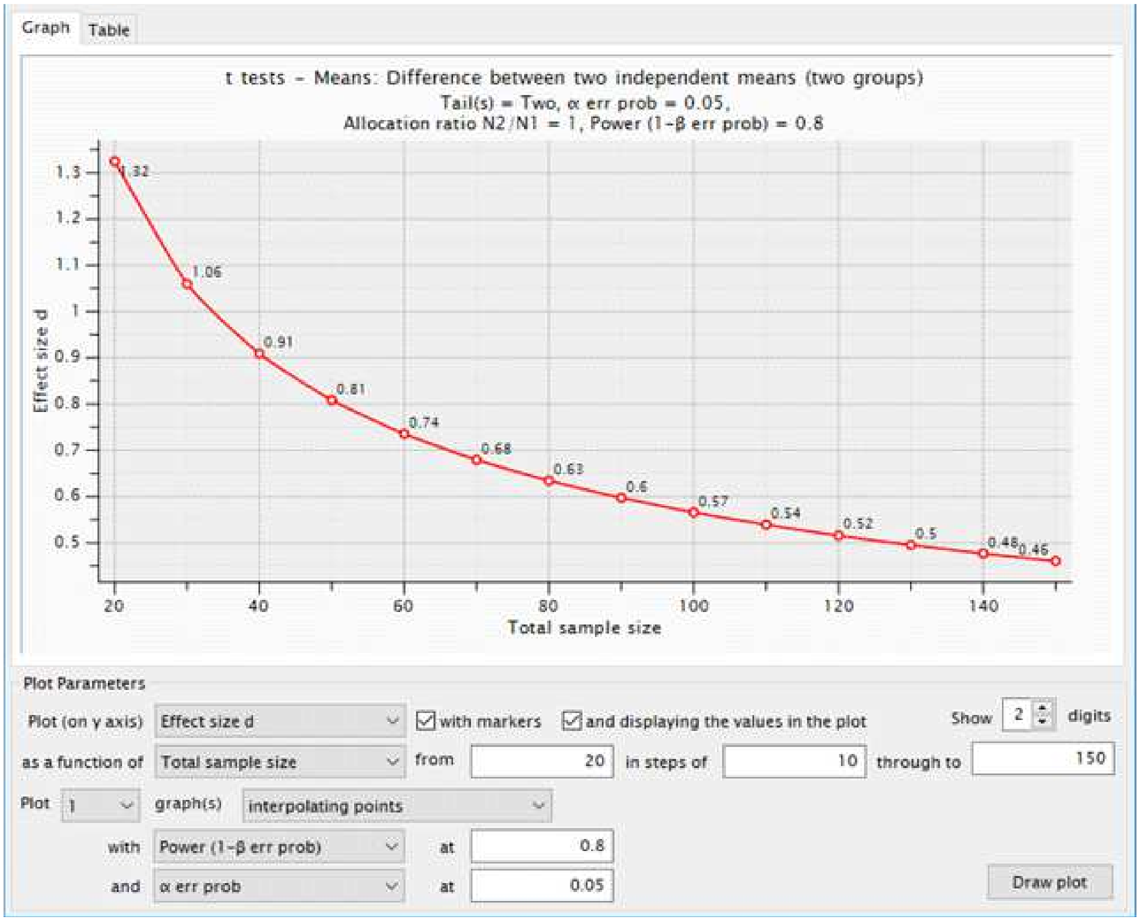


Figure 4. Z-test logistic regression sample size curve.

The preliminary review of the 2014–2016 BRFSS code book indicated that the IV of interest, home ownership, was measured and included in the data set (BRFSS, 2016). *Home* was defined as the place where a person or family lives most of the time or years. Home ownership was captured and operationalized with this question: Do you own or rent your home? Based on the information recorded in the 2014–2016 BRFSS data set, of 486,303 individuals who responded to the home ownership questions, 347,967 (71.55%) reported ownership of their homes and a weighted percentage of 66.25% (BRFSS, 2016). On the other hand, 114,264 (23.50%) respondents reported renting their home, a weighted percentage of 27.46% (BRFSS, 2016). For other living arrangements, 21,216 (4.36%) people reported other living arrangements, a weighted percentage of 5.56% (BRFSS, 2016). For those who did not know or were not sure about their housing status, 667 (0.14%) people reported their housing status as “don’t know,” a weighted percentage of 0.20% (BRFSS, 2016). Overall, 2,180 (0.45%) respondents refused to indicate their home ownership status, a weighted percentage of 0.54% (BRFSS, 2016). Finally, a total of nine (0.002%) participants did not respond to the question (BRFSS, 2016).

Preliminary review of 2014-2016 BRFSS code book also indicated that the confounding variable, income, was captured and included in the data set and was operationalized with the following question: ‘Is your annual household income from all sources’ listed in the options below (BRFSS, 2016), see Table 3 for more detail. Obesity is quantified by the BMI calculation and a function of weight in kg divided by height in m^2. The BMI categories are grouped into 25.0–29.9 kg/m^2 for overweight and ≥ 30.0 kg/m^2 for obesity measurements (Tsai, Lv Xiao, & Ma, 2016; World Health Organization, n.d.). The question about weight was stated in the 2016 BRFSS survey as follows: ‘*About how much do you weigh without shoes*’? Also, in the 2016 BRFSS, some respondents self-reported their heights in meters and centimeters when asked the following question: ‘*About how tall are you without shoes?’*. For the 2016 BRFSS, weight was documented in pounds and kilograms and height in feet and inches and meters and used it to calculate BMI as depicted in Table 4.

Table 3

Income Levels

Code Value	Income Category	Frequency	Percentage	Weighted percentage
1	Less than $10,000	19,855	4.11	4.96
2	Less than $15,000 ($10,000 to < $15,000)	21,838	4.53	4.33
3	Less than $20,000 ($15,000 to < $20,000)	30,913	6.41	6.63
4	Less than $25,000 ($20,000 to < $25,000)	37,943	7.86	7.86
5	Less than $35,000 ($25,000 to < $35,000)	44,076	9.13	8.74
6	Less than $50,000 ($35,000 to < $50,000)	58,349	12.09	11.37
7	Less than $75,000 ($50,000 to < $75,000)	64,947	13.46	12.55
8	$75,000 or more	127,081	26.34	27.47
77	Don't know/Not sure	35,338	7.32	8.24
99	Refused	42,177	8,74	7.85
Blank	Not asked or Missing	3,786	–	–

Table 4

BMI Measurements Distribution

Code Value	BMI Category	Frequency	Percentage	Weighted Percentage
1	Underweight BM1<18	7,530	1.69	1.98
2	Normal Weight BMI 18 to <25	142,110	31.81	33.20
3	Overweight BMI ≥25 to <30	161,282	36.11	35.24
4	Obese BMI ≥30	135,765	30.39	29.58
blank	Don't know/Refused/Missing	39,616	–	–

The unit of analysis for this study was the association between an area level factor and obesity are African American and Caucasian women living in Michigan. Therefore, it is important to describe operationalization of race of interested reported in the 2016 BRFSS data. Table 5 contains the frequency distribution for all the race categories documented by the NHANNES study. The five main categories included Caucasian; or African American; American Indian or Alaskan Native; Asian, and Native Hawaiian or Pacific Islander. The remaining categories included Other (for those not belonging to the five main categories), No preferred race, multiracial, and those who Refused to identify This research is based on the race/ethnicity categorization as depicted in (see Table 12)

Table 5

Race Distribution

Code Value	Race Group	Frequency	Percentage	Weighted Percentage
1	Caucasian	396,868	81.61	72.76
2	African American	42,962	8.83	12.69
3	American Indian or Alaskan Native	9,539	1.96	1.81
4	Asian	11,604	2.39	5.39
5	Native Hawaiian or other Pacific Islander	3,061	0.63	0.42
6	Other race	10,044	2.07	3.17
7	No preferred race	1,394	0.29	0.28
8	Multiracial but preferred race	1	0.00	0.00
77	Don’t know/not sure	3,801	0.78	1.46
99	Refused	7,025	1.44	2.03
blank	Missing	4	-	-

Age is one of the selected confounding variables in this study. The study unit of analysis included women ages 18 years and older who are living in the Michigan at the time of when the 2016 BRFSS was conducted. The preliminary review of the 2016 BRFSS code book shows the age distribution of the women in Table 6 who participated in the survey from whom the samples for this study was selected. Education is one of the confounding variables selected in this study. The preliminary review of the 2016 BRFSS code book shows the level of education in Table 7 reported by women who participated in the survey.

Table 6

Age Distribution

Code Value	Age Group	Frequency	Percentage	Weighted Percentage
1	18 to 64 years	308,872	63.51	78.56
2	65 years or older	170,734	35.11	19.91
3	Don’t know/Refused/Missing	6,697	1.38	1.23

Table 7

Educational Level

Code Value	Education Level	Frequency	Percentage	Weighted percentage
1	Did not graduate High School	37,908	7.80	13.90
2	Graduated High School	136,626	28.09	28.04
3	Attended College or Technical School	133,368	27.42	40.93
4	Graduated College or Technical School	176,627	36.32	26.38
9	Don’t know/Not sure/Missing	1,774	0.36	0.45

Methodology

Population

The target population for this study are adult African American and Caucasian women ages 18 years and older living in Michigan. These women was selected from the 2016 BRFSS survey data set. This secondary data set consists of adult women who self-identified as obese and who rent or own house.

Sampling and Sampling Procedures

Based on preliminary analysis of 2016 BRFSS code book, the 2016 BRFSS sampling was conducted via either a call through cell phone or landline (BRFSS, 2016). The women were randomly selected (BRFSS, 2016). These women included adults ages 18 years and older (BRFSS, 2016). Participants were asked to identify whether the type of phone currently being used including a cell phone or a landline telephone (BRFSS, 2016). Participants were also asked to identify if the contact number used was the correct phone number, and whether they resided in a private residence (such as a house or apartment) or a college housing (BRFSS, 2016). Participants were asked to identify state they are currently living (BRFSS, 2016). The rest of the questions were asked accordingly.

Weighting methodology. CDC used cell or mobile phones for BRFSS sampling, for that reason, a new weighting methodology (raking or iterative proportional fitting) replaced older versions (post-stratification; BRFSS, 2016). With the raking method, age, gender, race/ethnicity, and other demographic variables such as education attainment, marital status, house tenure (property ownership or rental status), and telephone ownership were included in the survey response (BRFSS, 2016; CDC, 2012). According to the CDC, 2012 report, including cell/mobile phones has facilitated the inclusion of a broader demographic and ultimately provided a better reflection of the nation's health status, maintains survey coverage and validity. The new weighting methods adjusts survey data for differences based on demographic characteristics of the respondents (BRFSS, 2016). This also reduces the potential for certain biases and increases representativeness of the sample estimates (BRFSS, 2016). The 2016 BRFSS ranking weighting methodology was calculated using the design weight and raking approach (BRFSS, 2016; CDC, 2016). The design weight calculation approach is shown below:

*Design Weight = Stratum weight (STRWT) * 1/* number of residential telephone numbers in respondent's household (*NUMPHON) * Number of adults in the respondent's household (NUMADULT)*

The design weight is a function of the stratum weight and inverse of number of residential telephones numbers and number of adults in the overlapping sample frames. The design weight was then truncated based on quartiles within the geographic region and that was used as the raking input weight (CDC, 2016). The stratum weight accounted for differences in the basic probability of selection among strata (subsets of area code or prefix combinations) which is the inverse of the sampling fraction of each stratum between strata and regions (CDC, 2016). The BRFSS defined strata by subsets of area code or prefix combinations (CDC, 2016).

The BRFSS defines regions by the boundaries of government entities (BRFSS, 2016; CDC, 2016). The STRWT was calculated using the variables shown below (BRFSS, 2016; CDC, 2016):

- Number of available records (NRECSTR) and the number of records selected (NRECSEL) within each geographic strata and density strata.
- Geographic strata (GEOSTR), could be the entire state or a geographic subset (e.g., counties, census tracts).
- Density strata (DENSTR) indicating the density of the phone numbers for a given block of numbers as listed or not listed.

Within each GEOSTR*DENSTR combination, the STRWT was calculated from the average of the NRECSTR and the sum of all sample records used to produce the NRECSEL. The stratum weight is equal to NRECSTR/NRECSEL (BRFSS, 2016; CDC, 2016). While 1/NUMPHON2 represented the inverse of the number of residential telephone numbers in the respondent's household. NUMADULT represents the number of adults 18 years and older in the respondent's household (BRFSS, 2016; CDC, 2016).

The final weight reflects the design weight raked into 8 margins (age group by gender, race or ethnicity, education, marital status, house tenure, gender by race or ethnicity, age group by race or ethnicity, and phone ownership) (BRFSS, 2016; CDC, 2016). If geographic regions are included, four additional margins (region, region by age group, region by gender, region by race or ethnicity) are included (BRFSS, 2016; CDC, 2016). For counties with 500 or more respondents, BRFSS included four additional margins (county, county by age group, county by gender, and county by race or ethnicity) (BRFSS, 2016; CDC, 2016). The final weight of landline telephones and cellular telephones in the population (LLCPWT) reflected the final weight assigned to each respondent (BRFSS, 2016; CDC, 2016).

The 2016 MiBRFSS is a sub-sample of the 2016 BRFSS data set (BRFSS, 2016; CDC, 2016). The total number of participants enrolled or participated in the 2016 MiBRFSS survey was 12,024 subjects. The total number of participants who completed the core interview survey was 12,024 (landline = 4,797 and cell phone = 7,227) (BRFSS, 2016; CDC, 2016). The preliminary review of the 2016 MiBRFSS publicly available codebook material (non-data) shows that, within the 2016 the sample of landline telephone numbers utilized to collect data were chosen via a list-assisted, random-digit-dialed methodology using disproportionate stratification which was based on phone bank density (BRFSS, 2016; CDC, 2016). The information captured in the MiBRFSS included the phone numbers directory listing status (BRFSS, 2016; CDC, 2016).

Just as the national BRFSS, iterative proportional fitting or raking was the weighting methodology used in the 2016 MiBRFSS data set thus rendering the data capable of representing the Michigan adult population (BRFSS, 2016; CDC, 2016). Raking ensures that conclusions or estimations drawn would include demographic variables such as race/ethnicity, education level, marital status, age by gender, gender by race/ethnicity, age by race/ethnicity, and renter/owner status of the target population. The 2016 MiBRFSS data included state-specific, population-based prevalence estimations, calculated for indicators of health status, health risk behaviors, clinical preventive practices, and chronic conditions among adult population in Michigan (BRFSS, 2016; CDC, 2016). The 2016 MiBRFSS criterion for exclusion removed participants who refused to answer a question (BRFSS, 2016; CDC, 2016). Participants who responded "Don't Know/Not Sure" were also removed from the denominator unless indicated otherwise

(BRFSS, 2016; CDC, 2016). For CDC purposes, the initial data manipulation was conducted using the SAS-Callable SUDAAN, a statistical computing program designed for complex sample surveys (BRFSS, 2016; CDC, 2016).

Data Analysis Plan

The intended data analysis plan covers the following important areas that was employed in several of the data storage, operationalization, transformation, manipulation, and analysis to help produce valid interpretation of the findings. The data analysis plan in this research context is the roadmap for how the data set in this study was organized and analyzed. The set data analysis plan was useful in achieving key objectives intended in a study. Some of the key objective are not only limited to appropriately addressing the posed research questions, but rather ensuring that the appropriate design method, and statistical approaches were used in amazing the information generated from the secondary data. Also, the data plan included the approaches used in selecting and analyzing key confounders and covariates to help address the validity and limitations of the study. For the purpose of this study, SPSS software was used for the descriptive and inferential analyses. Binary logistic regression was used for the statistical analysis.

Binary logistic regression. Binary logistic regression is often referred to simply as logistic regression and it is used for the analysis of 2 variables (bivariate) (BRFSS, 2016; CDC, 2016; Warner, 2013). Binary logistic regression is used when variables are dichotomous (BRFSS, 2016; CDC, 201; Warner, 2013). For this study, obesity measurement is dichotomous where a participant is either obese or not obese (BRFSS, 2016; CDC, 2016; Warner, 2013). For this study, participants are either adult African American females 18 years and older who are either obese or not obese or adult Caucasian females 18 years and older who are either obese or not obese); and either group membership is mutually exclusive (BRFSS, 2016; CDC, 2016;

Warner, 2013). Meaning participants cannot belong to more than one group (BRFSS, 2016; CDC, 2016; Warner, 2013). Also, with a binary logistic regression, the IV can be a scale/continuous or categorical variable (Warner, 2013). For this study, age and income confounders are both continuous variables but was grouped into an ordinal variable while both obesity and area-level factor (residence status: rent or own) are nominal variables.

Binary logistic regression assumptions. Binary logistic regression rules include the application of the following assumptions (Warner, 2013). The sample size (N) must at least be 10 times the value of k, where k is the number of predictor (independent) variables (Warner, 2013). Cells with an expected frequency less than five should be few in both the categorical and outcome variable (Warner, 2013). The study should be designed to have sufficient statistical power. statistical power, 80% or above (Warner, 2013). Data should be screened for the presence of extreme outliers and corrected as needed (Warner, 2013).

According to Green and Salkind (2014), to determine the significance test variables in bivariate linear regressions or binary logistic regression, two alternative sets of assumptions can be applied (Green & Salkind, 2014). First, the assumptions for a fixed effects model or assumptions or the random effects model should be met (Green & Salkind, 2014). The fixed effect model assumptions are preferred in experimental studies because if the fixed effects model assumptions are met, then a linear or nonlinear relationship exists between the variables, the predictor and criterion variables (Green & Salkind, 2014). However, if only the assumption for a random effects model is met, then only a linear statistical association exists between variables (Green & Salkind, 2014). Assumptions for the fixed effect model are as follows:

Assumption 1: The DV is normally distributed in the population for each level of the IV (Green & Salkind, 2014). If this assumption is forfeited then the sample size under investigation must be large enough to generate accurate p values (Green & Salkind, 2014). If sample size is small and the assumption of normality is not, it is more likely that the study will not generate valid p values and the power of the study will insufficient (Green & Salkind, 2014).

Assumption 2: The population variances of the DV are the same for all levels of the DV (Green & Salkind, 2014). If the assumption is not met, the p value generated will not be statistically significant, possibly Type II error (Green & Salkind, 2014).

Assumption 3: The cases represent a random sample from the population, and the scores are independent of each other from one individual to the next (Green & Salkind, 2014). If this assumption is not met, then the significance for the logistic regression test will generate invalid p values (Green & Salkind, 2014).

Rationale for using binary logistic regression. The standard measures or criteria relevant to performing the binary logistic regression are met for the current study because the obesity and house ownership status are nominal variables as described. Income, education, and age are ordinal variables. These conditions satisfied the key assumptions of binary logistic regression (Statistics Solutions, 2016).

The Statistical Test Values

For the minimum sample size estimation required to generate sufficient statistical power, the G*Power software was used for the calculation. For the sample size estimation, predetermined effect size value used was 2.0. The beta value for the Type II error used was 20% (0.20) and the corresponding statistical power value used was 80% (0.80). The predetermined alpha value for the estimation of Type I error used was 5% (0.05) while the corresponding confidence level used was 95% (0.95).

Research Questions and Hypotheses

RQ1: What is the association between the area-level factor residential status (own or rent), and obesity risk among adult African American women after controlling for income, education, and age?

$H_0$1: There is no association between the area-level factor residential status (own or rent) and obesity risk among adult African American women after controlling for income, education, and age.

H_a1: There is an association between the area-level factor residential status (own or rent) and obesity risk among adult African American women after controlling for income, education, and age.

RQ2: What is the association between the area-level factor residential status (own or rent) and obesity risk between adult African American and Caucasian women after controlling for income, education, and age?

$H_0$2: There is no association between the area-level factor residential status (own or rent) and obesity risk between adult African American and Caucasian women after controlling for income, education, and age.

H_a2: There is an association between the area-level factor residential status (own or rent) and obesity risk between adult African American and Caucasian women after controlling for income, education, and age.

Threats to Validity

Internal and External Validity

Threats to the external and internal validity of a cross-sectional design study exist. Validity is referenced as the ‘lack of systemic error’ (Rothman, Greenland, & Lash, 2008).

According to (Carlson & Morrison, 2009) internal validity describes the strength of the inferences (conclusions) drawn from a study. Internal validity is useful in evaluating accuracy of the effects of the exposure or intervention on the outcome measure. Once an internal validity is established and external validity can be determined (Rothman et al., 2008; Baldwin, 2018). When the change in the outcome measure is due to a systematic error establishing an internal validity was problematic (Rothman et al., 2008; Baldwin, 2018). When a study lacks a control group or when the two groups being studied are not comparable in all measures, the internal validity of a study was threatened (Rothman et al., 2008; Baldwin, 2018). For example, in this study, if the subject characteristics or comparison categories between African American women and Caucasian women differ, the internal validity of the study was threatened as a result of selection bias. Internal validity can also be threatened by mortality over time especially in longitudinal studies (Baldwin, 2018). The rate of mortality or subject loss (attrition) between groups being studied differs substantially, the internal validity of a study maybe compromised (Rothman et al., 2008; Baldwin, 2018).

Differences in subject location (e.g., access to technology, geospatial area etc.) can also threatened internal validity ((Rothman et al., 2008; Baldwin, 2018). The differences in access to a landline or cell/mobile telephone between African American and Caucasian women living in Michigan can affect the internal validity, which will induce selection bias. However, CDC used raking and weighting measures to conduct the survey and generate 2016 BRFSS data. Thus, the applied approaches greatly minimized such threat to validity.

External validity references the generalizability of study results (Rothman et al., 2008; Baldwin, 2018). When the cause–effect or correlation associations from a specific study can be generalized to the entire populations and conditions, then the study is deemed externally valid

(Carlson & Morrison, 2009). Therefore, external validity evaluates the extent to which the conclusions drawn from a study would be similar (replicable) for other persons in a different study, place, and time (Carlson & Morrison, 2009). The quality, internal and external validity established in this study was based on the data integrity established in the 2016 BRFSS data (BRFSS, 2016). The BRFSS data approach is a credible source (BRFSS, 2016). In 1984, CDC established the BRFSS, and 15 states participated in a monthly data collection (CDC, 2014). Next the CDC created a standard core questionnaire for data collection that is comparable across states (CDC, 2014). Initial topics included smoking, alcohol use, physical inactivity, diet, hypertension, and seat belt use (CDC, 2014). By 1993, the BRFSS become a nationwide surveillance system (CDC, 2014). The existing questionnaire was introduced to include rotating fixed core and rotating core questions and up to five emerging core questions (CDC, 2014). In 1993, about 100,000 interviews were conducted (CDC, 2014). In 2002, the first biannual BRFSS Expert Panel Meeting was held, which included approximately 20 survey statisticians, methodologists, and operational experts to discuss the barriers in survey research and its implications for BRFSS (CDC, 2014). Subsequently in 2004, 2006, and 2009, similar meetings were held with the goal of developing options and prioritizing recommendations for maintaining data quality amidst societal and technological changes (CDC, 2014).

By 2008, the BRFSS introduced the cell phone survey (CDC, 2014). Through this method, the BRFSS was able to reach population groups that were previously inaccessible via landline access; thereby producing a more representative sample and higher quality data (CDC, 2014). By 2011, data collected via cell phone could be accessed by the public (CDC, 2014). In that same year (2011), over 500,000 surveys were completed reinforcing the BRFSS as the largest telephone survey in the world (CDC, 2014). Also, new weighting methodology (raking, or iterative proportional fitting) replaced older versions (CDC, 2014). With the raking method, age, gender, race/ethnicity, and other demographic variables such as education attainment, marital status, tenure (property ownership), and telephone ownership were included (CDC, 2014). BRFSS remains the gold standard of behavioral surveillance (CDC, 2014). Today, data are collected monthly from all 50 states, including District of Columbia, American Samoa, Palau, Puerto Rico, the U.S. Virgin Islands, and Guam (CDC, 2014). CDC Pledges to work closely with state and territorial partners to ensure that the BRFSS continuously provides data that are useful for public health research, practice, and state and local health policy decision making (CDC, 2014).

In addition, specific instruments used in the BRFSS have been previously tested to determine its reliability and validity (CDC, 2014). For example, the validity and reliability of the BRFSS physical activity instrument questions are useful in classifying groups of adults within recommended levels of vigorous activity as defined by Healthy People 2010 (Yore, Ham, Ainsworth, Kruger, Reis, & Macera, 2007). It also showed that repeated use of these questions over time helps in identifying trends in physical activity (Yore et al., 2007). BRFSS data in general has been reliable and a tool for conducting research and surveillance both in academia, public health, and epidemiology (Stein, Lederman, & Shea, 1993).

Summary

African American and Caucasian women who live in Michigan was included in this study. The women included in the study are those ages 18 years and older. Women included was randomly selected and not randomly assigned. Homeless and pregnant women will not be included in the study. Women with familial history of obesity will also be excluded because the obesity outcome could be attributed to the family history rather than residence status (‘own’ or ‘rent’ status). The data set that was used is a secondary data generated by the BRFSS in 2016, which contained a subset of data set called MiBRFSS that represent individuals living in Michigan. The Walden IRB approval was obtained before the secondary data is used and only de-identified data sets were analyzed and published. Once the data is obtained or downloaded, it was stored in a password protected and secured computer. Both obesity and area-level factor (residence status) are nominal variables. A nominal variable fit the assumption of binary logistic regression (Statistics Solutions, 2016). The analysis was performed in two parts, the descriptive and inferential analyses using a binary logistic regression. This section of the dissertation lays the foundation for the statistical analysis and results and conclusion sections that was discussed in Chapter 4 and 5 respectively.

Chapter 4: Results of Statistical Analyses

Introduction

The goal of this study was to assess the direction and strength of the association between the area-level risk factor (housing status) and the risk of becoming obese for women living in Michigan. For this assessment, statistical analyses—specifically multiple logistic regression analyses—were performed using the presence or absence of obesity as the dichotomous outcome variable. Here the participants' residence status and their race were the predictor variables being investigated, while age, income level, and education level were included as controlling variables. The data from the 2014–2016 BRFSS cross-sectional survey results for the state of Michigan were used to perform statistical analyses with the software program SPSS. The research questions along with corresponding hypotheses developed for this study are:

RQ1: What is the association between the area-level factor residential status (own or rent) and obesity risk among adult African American women after controlling for income, education, and age?

$H_0 1$: There is no association between the area-level factor residential status (own or rent) and obesity risk among adult African American women after controlling for income, education, and age.

$H_a 1$: There is an association between the area-level factor residential status (own or rent) and obesity risk among adult African American women after controlling for income, education, and age.

RQ2: What is the difference between the association of area-level factor residential status (own or rent) and obesity risk for adult African American relative to adult Caucasian women after controlling for income, education, and age?

$H_0 2$: There is no difference between the association of area-level factor residential status (own or rent) and obesity risk for adult African American relative to adult Caucasian women after controlling for income, education, and age.

$H_a 2$: There is a difference between the association of area-level factor residential status (own or rent) and obesity risk for adult African American relative to adult Caucasian women after controlling for income, education, and age.

This fourth chapter of the dissertation contains the data collection process, including acquiring and subsequent treatment of the data; details of the statistical analyses performed; and the results generated from the analyses conducted. It starts with a brief description of secondary data that were obtained from the 2014–2016 BRFSS cross-sectional survey report and how these data were accessed, what was done in preparation for the statistical analyses performed, including the data acquisition, and the data preparations steps. This is followed by details of the descriptive statistics of all the dependent, controlling, and IVs relevant to this study. Lastly, the chapter ends with details of the analyses conducted to answer the two research questions, including the results of each analysis and how these results are interpreted in relation to the overall objective of the research.

Data Collection

BRFSS data are collected annually using ongoing phone (landlines and cellphones) surveys to collect health data from residents of the entire United States. This survey collection effort started in 1984 with 15 states and now includes all 50 states, the District of Columbia, and all three U.S. territories (CDC, 2020). Over 400,000 interviews are conducted annually, which is more than any other health survey system worldwide (CDC, 2020). CDC manages these surveys and they are conducted by the respective state health departments personnel for each state. The participants are questioned on a number of issues, including demographics (age, race, gender, marital status, etc.) as well as other relevant information related to their health history and status. Following collection of the data, the CDC statisticians use specific design-weighting and stratum-weighting processes (outlined in Chapter 3) to make the data more representative of the respective state's population, while at the same time minimizing any bias that may have occurred during the collection phase. The weighting in the final reports reflects the data that have been weight-adjusted based on several demographic characteristics, including age, race, sex, marital status, and location (CDC, 2017). These weighted data are in the final report made available as electronic public data files, which were used for this study.

Data Cleaning

The electronic public BRFSS files are available as an ASCII or as an SAS formatted document on the CDC website. The 2014–2016 BRFSS file segment was downloaded and saved to the local computer and opened, using the Version 25 of the SPSS software. Because these files are precleaned and pretreated by the statisticians at the CDC prior to being available for public use, there was no further cleaning required. However, prior to the statistical analyses in this research, the file was filtered twice, by state and by gender (state = 26 and by sex = female) to include only the data from adult female residents in Michigan. This filtered file was saved as the final working file and was the version used for all statistical analyses conducted in this study.

Results of Data Analysis

Descriptive Analysis

Valid sample size. After filtering the data set (for state and for gender), there were 12,024 participants from the state of Michigan, and of that number, only 6,663 were (18 years or older) adult women. The income-level variable had the largest number of participants for whom information was missing (1,268), followed by BMI (715), while residence (62) and education (9) had much less missing. With all the missing values accounted for, the number of valid participants, for whom there was information on all the relevant variables, amounted to 5,369 (see Table 8). This value was larger than the required sample size of 113, as determined by the G*Power sample size estimation (see Chapter 3).

Table 8

Table of Valid Number for Each Variable

	Valid	Missing
Age	6,663	0
Income level	5,395	1,268
Preferred race	6,663	0
Education level	6,654	9
Residence	6,601	62
Body mass index	5,948	715
Valid N (listwise)	5,369	

Control variables measures of central tendency. The age variable, as reported in the data set, ranged from 18 to collapsed at 80, and the average age of the participants was determined to be 55.22 years, with a standard deviation of 17.271. The histogram of the age values indicated that the values were effectively normally distributed, although the collapsed at 80 bar erroneously implied a bimodal type distribution (Figure 5). Fortunately, this collapsed value did not affect the results, as the age variable was ultimately used as a categorical variable in both the bivariate and the logistic regression analyses. This collapsing also did not cause any undue skewness or kurtosis as the mean and the true mode appeared to be the same (approximately 55 years). Collapsing the end values (at 80 years and above) did render the determination of the median unreliable.

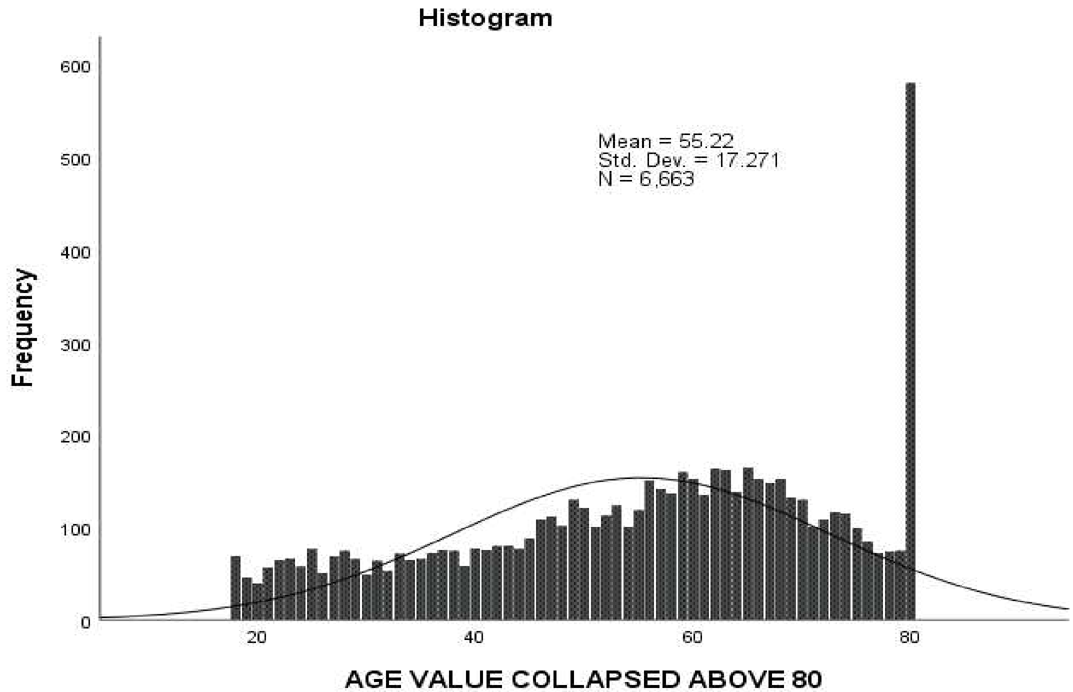


Figure 5. Histogram of age distribution.

An alternative categorical variable was created from the original continuous age variable for use in the bivariate and multiple logistic regression analyses. For the frequency distribution, because there were no missing values, the frequency and the valid frequency were the same. As seen in Table 9, of the six groups into which the values were divided, the category for ages 64 years and older (> 64) became the group with the highest frequency (34.7%), followed by the category just below it, those between ages 55 and 64 (22.0%). There were smaller representations of younger age groups, with 45 to 54 accounting for only 16.6%, and 35 to 44 representing 11.1% of the sample (Table 9). Subjects under 34 years represented 15.7% of the total population, with the those 25 to 34 making up 9.6%, and the remaining 6.0% were 18 to 24. Dividing the populations into thirds—over 64 at 34.7%, 45 to 64 at 38.6%, and under 45 at 26.7%—showed a relative even distribution.

Table 9

Frequency Table for Age Groups

Age groups	Frequency	Valid percent	Cumulative percent
18–24	403	6.0	6.0
25–34	641	9.6	15.7
35–44	741	11.1	26.8
45–54	1103	16.6	43.3
55–64	1463	22.0	65.3
> 64	2312	34.7	100.0
Total	6663	100.0	

The income level variable was included as it has been proven to be a moderate predictor of obesity outcome in previous studies (Bentley, Ormerod, & Ruck, 2018; Conway et al., 2018; Kim & von dem Knesebeck, 2018). The distribution of income among this sample data set reflected an inequality, as a little over one-third (35.0%), the highest frequency, were earning more than $50,000 a year, while the rest of the sample was divided almost equally among the remaining four income level groups (Figure 6). When these remaining respondents were divided into four subgroups based on increments of $10,000, the largest group ($15,000 - < $250,000) was 14.8% of the subjects, while the other three (< $15,00; $25,000 - $35,000; and $35,000 - < $50,000) made up of 9.3%, 10.0% and 11.8% respectively of the total sample (Table 10). The precision of these frequency numbers, representing income distribution, could be challenged as income information was missing for almost one-fifth (19.0%) of the participants.

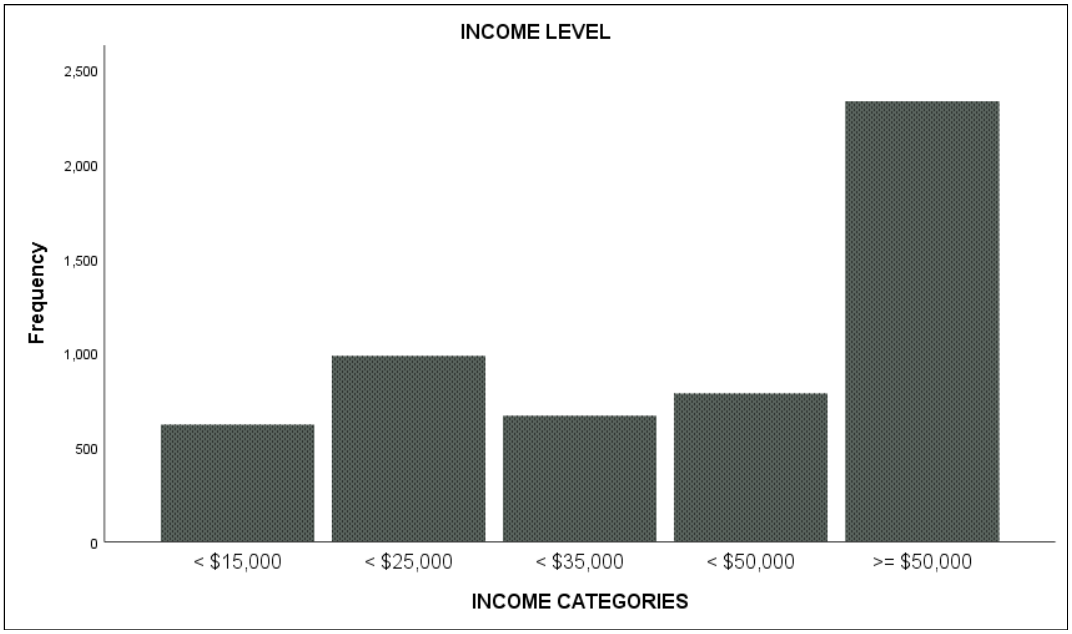


Figure 6. Bar chart of income level categories.

Table 10

Frequency Table of Income Categories

	Frequency	Percent	Valid Percent	Cumulative Percent
< $15,000	621	9.3	11.5	11.5
< $25,000	985	14.8	18.3	29.8
< $35,000	668	10.0	12.4	42.2
< $50,000	786	11.8	14.6	56.7
≥ $50,000	2335	35.0	43.3	100.0
Total	5395	81.0	100.0	
Missing	1268	19.0		
Total	6663	100.0		

Like the distribution of income level, the distribution of education level also reflected a sample data set made up of higher than average economic status, as the majority (67.2%) of the subjects had earned at least some college credit (Figure 3). Over one-third (34.5%) of the group had acquired a degree or certification from either a liberal arts college or a technical college (Table 11). For some reason, the data collection report did not distinguish between those with a liberal arts college and technical college degree, and so this study was unable to do so as well. For those without a degree, a vast majority were at least high school graduates, as only 4.5% of the sample did not graduate high school (Figure 7). Similar to the income level distribution, for education level the sample could effectively be divided into three, almost equal categories, *high school diploma* (28.0%); *some college* (32.6%), and *college/technical graduates* (34.5%).

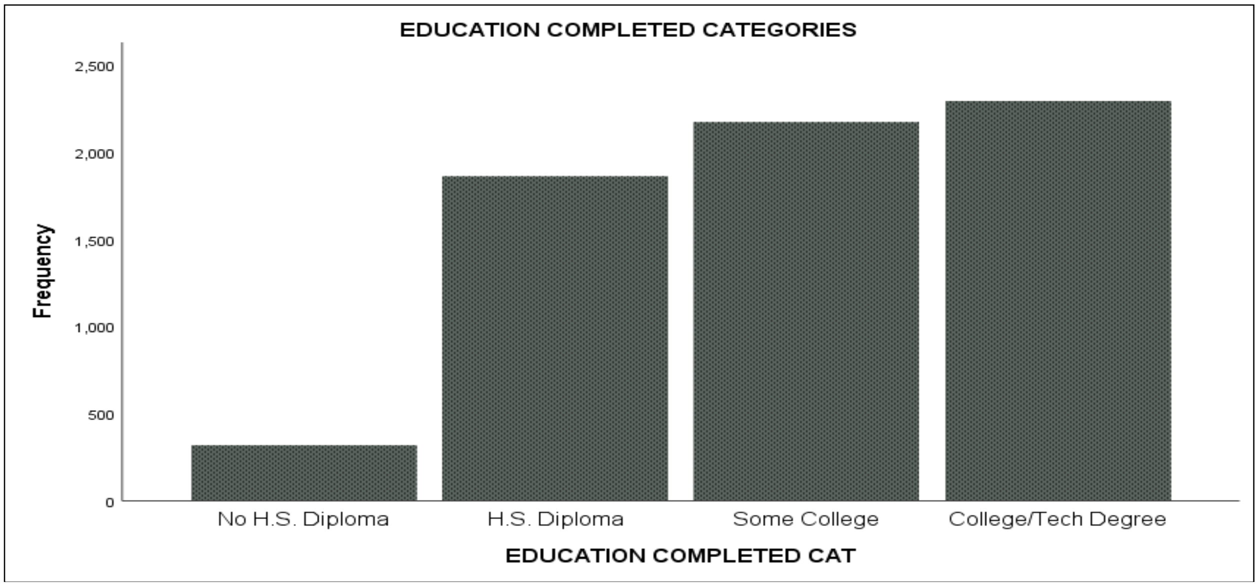


Figure 7. Bar chart of education completed categories.

Table 11

Frequency Table of Education Completed

Education Completed	Frequency	Percent	Valid Percent	Cumulative Percent
No high school diploma	319	4.8	4.8	4.8
High school diploma	1863	28.0	28.0	32.8
Some college	2174	32.6	32.7	65.5
College/tech grad	2298	34.5	34.5	100.0
Total	6654	99.9	100.0	
Missing	9	0.1		
Total	6663	100.0		

Predictor variables. The distribution of the race-ethnicity category was limited to four subgroups, *Caucasian* or *Caucasians*; *African Americans* or *African American*; *Hispanics*; and *Others* (Figure 8). From these categories 79.6% of the sample identified as *Caucasians*, 11.7% as *African Americans*, and 2.4 as % *Hispanics*. There were some 310 (4.7%) women who considered themselves not belonging to any of the three main races classes (African Americans, Caucasian, or Hispanics), and there was another 108 (1.6%) for whom the race-ethnicity information was missing (Table 12). These numbers indicated potential bias, as they differed from the census report of the distribution of races in the general public, but more closely resembled the percentages for the state of state of Michigan for the year 2016, in which Caucasians amount to 78.9%, African Americans 13.9%, and Hispanic 4.8% (U.S. Census Bureau, 2016). It should be noted that the percentage of Hispanic in this sample set is half of that in the official census report, and that this discrepancy persisted even after the weight-adjustment carried out by the statisticians at the CDC. However, since the research questions in this study dealt mainly with the comparison between the risk of obesity for African Americans relative to that for Caucasians, and the percentages of these two subgroups are somewhat reflective of that of the US population (African Americans: 13.9% vs.11.7% and Caucasians 78.9% vs. 79.6%), the validity of the results is maintained.

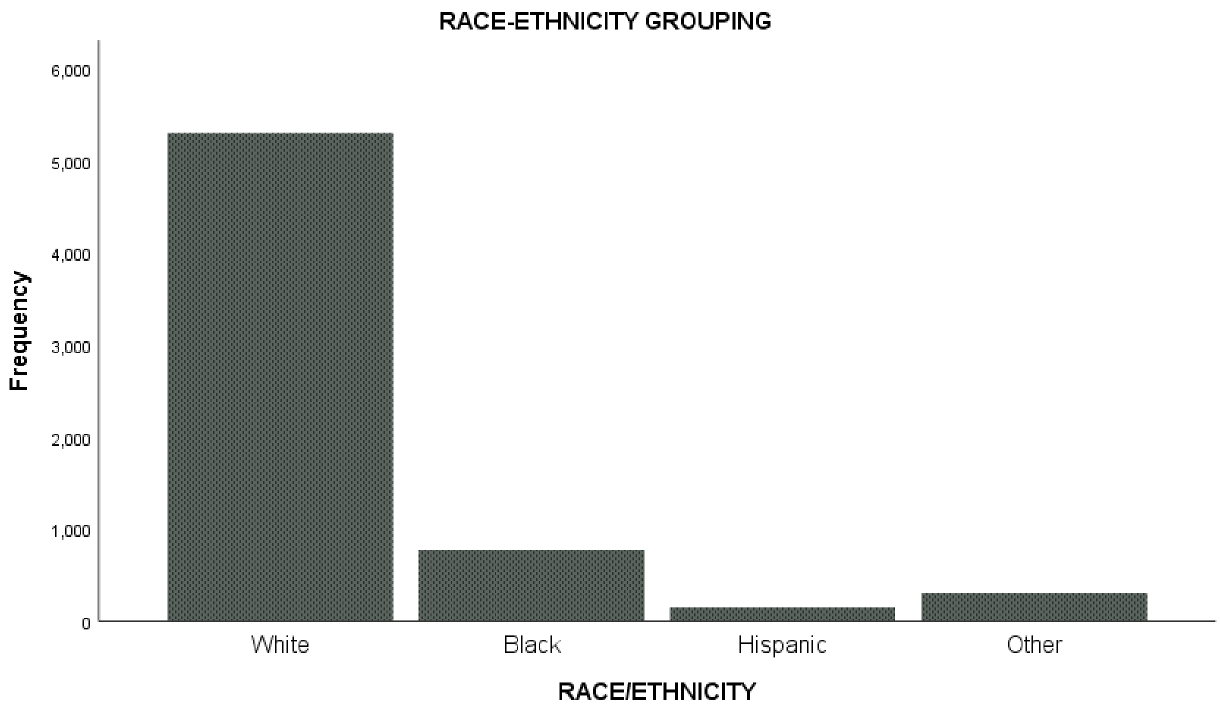


Figure 8. Bar chart of race subgroups.

Table 12

Frequency Table of Race Categories

Race	Frequency	Percent	Valid Percent	Cumulative Percent
Caucasian	5307	79.6	81.0	81.0
African American	779	11.7	11.9	92.8
Hispanic	159	2.4	2.4	95.3
Other	310	4.7	4.7	100.0
Total	6555	9.4	100.0	
Missing	108	1.6		
Total	6663	100.0		

The information in the RESIDENCE STATUS variable was based on the response to the question “Do you own or rent your home?” There were three possible responses- *Homeowner*, *Renter*, and *Other Arrangement* (see Table 13). The majority of subjects, almost three-quarters, reported being *Homeowners* (73.9%), while most of the remaining one-quarter identified as *renters* (21.9%), and only a very small percent considered themselves as having some *other arrangement* (4.2%). This unequal distribution in residence status is noteworthy as it may be another indication of a higher than average SES, which is not representative of the general US population. Also implied are possible interactions between the variables that reflect SES (such as income level with education level, or even that of race), which may affect the results of the statistical analysis (see Bivariate Analysis section). Fortunately, multiple logistic regression analysis, unlike linear regression, is robust enough to handle unequal distribution and interaction among the categories of a variable being tested (Nima, 2018).

Table 13

Frequency Table of Residence Status

	Frequency	Percent	Valid Percent	Cumulative Percent
Own	4879	73.2	73.9	73.9
Rent	1447	21.7	21.9	95.8
Other	275	4.1	4.2	100.0
Total	6601	99.1	100.0	
Missing	62	9.0		
Total	6663	100.0		

Outcome variable: BMI and obesity. The variable most pertinent to this research was the measure of body mass index (BMI). In BRFSS data set, BMI is reported as a continuous variable, in grams per cubic meters (decag/m^3) and had to be converted to the more familiar format of kg/m^3 by dividing by 100. The histogram generated from the BMI values did indicate a relatively normal distribution, with a mean of 28.28 and a 6.782 kg/m^3 standard deviation (Figure 10). The BMI values ranged from 14.38 to 79.71 kg/m^3, and due to some very high BMI values there was a measure right skewness in the histogram, causing the mean to be slightly larger than both the median and the mode (see Figure 10). However, these extremes in values were not a threat to the accuracy of the analysis, as BMI like the other continuous variable AGE, was utilized as a categorical variable in the descriptive analysis and as a dichotomous variable (see Figure 9) in the multiple logistic regression (MLR). For the dichotomous variable, *non-obese* were BMI<30 kg/m^3 and *obese* BMI>=30 kg/m^3. Given that MLR is probabilistic in nature it does not assume normality of distribution of the data values, it is resistant to the damage caused by outliers in other types of regression analysis *(*Stewart, 2018).

For the purposes of distribution investigation in the frequency table generation in the descriptive analysis, the BMI values were divided into five categories (Table 14). These five categories included underweight, normal weight, overweight, obese and morbidly obese. As there were enough morbidly obese individuals (BMI were over 40 kg/m^3) included in this data set, it necessitated the creation of a separate category for morbid or extreme obesity, which accounted for 5.9% of the total number of subjects with reported BMI. There were only four categories in the represented in the bar chart, underweight, normal weight, overweight and obese (Figure 11).

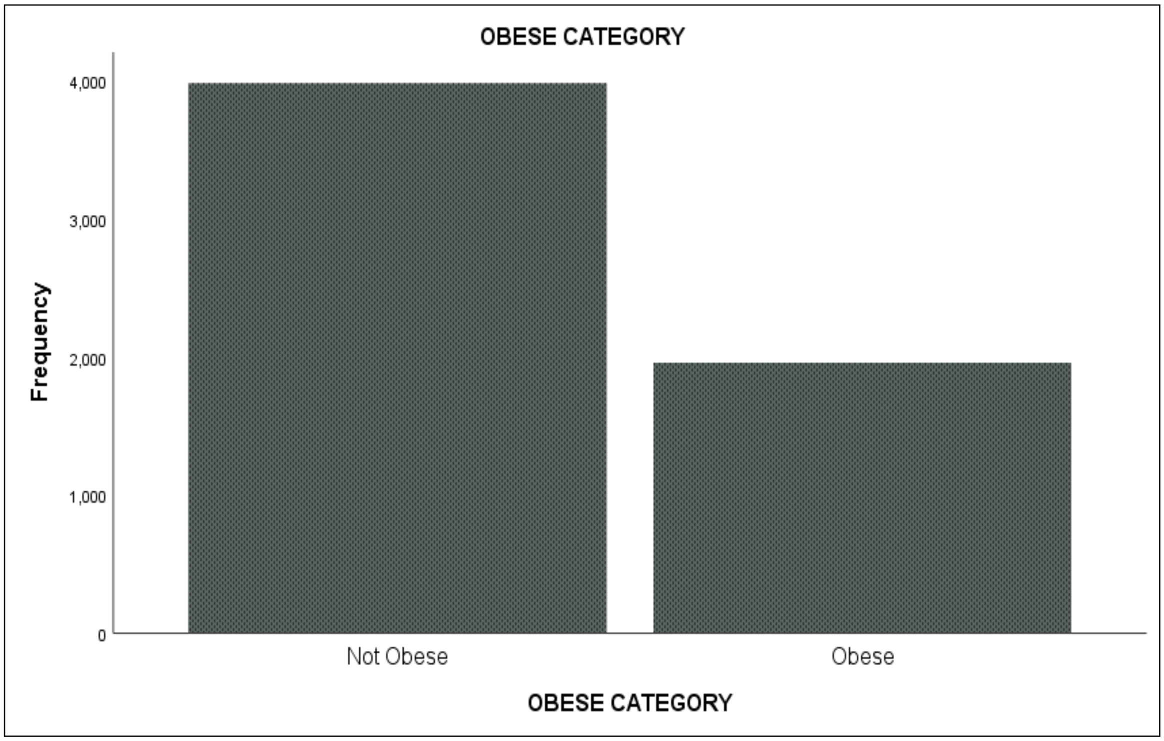


Figure 9. Bar chart of obesity distribution.

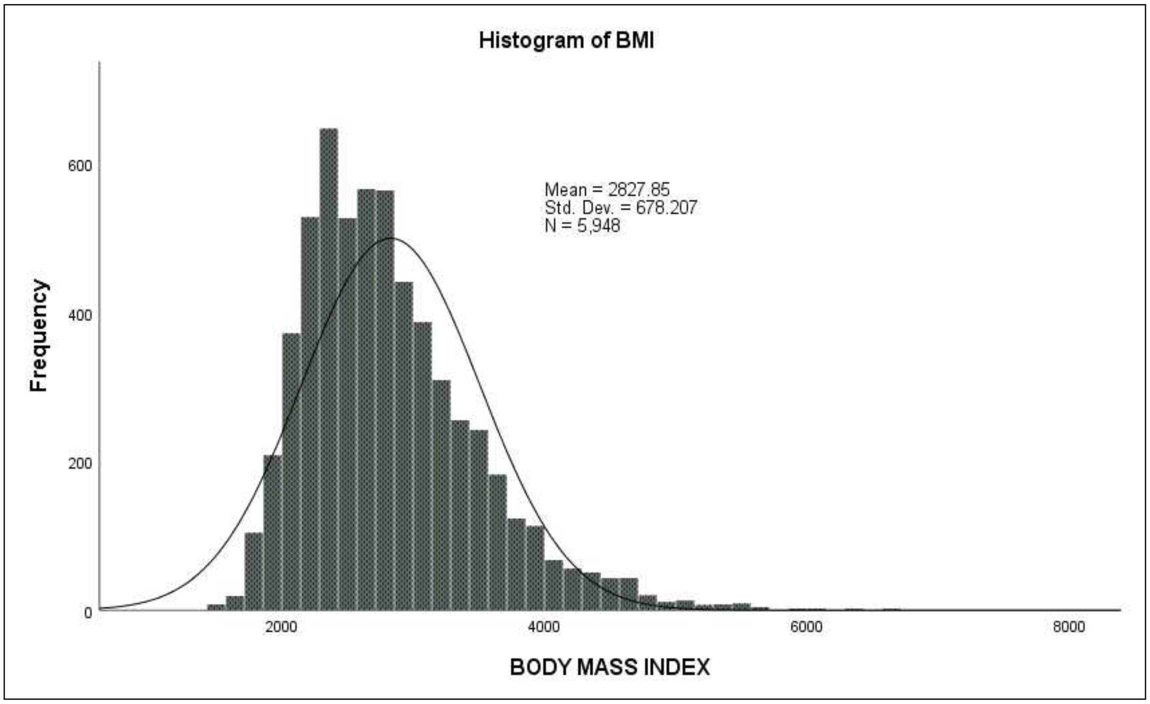


Figure 10. Histogram of BMI distribution.

The five categories for the BMI subgroups are listed as follows: underweight (BMI<18.5 kg/m^3), normal weight (BMI<25 kg/m^3), overweight (BMI<30 kg/m^3), obese (BMI<40 kg/m^3), morbidly obese (BMI>40 kg/m^3). These grouping are based on the BMI classification as established by the CDC, and based on those values, only 1.8% of the sample was underweight, and 30.7% was normal weight. The almost one-third of the sample (29.4%) were obese, and those that were obese some 17.6% (5.2% of the total sample) were morbidly obese (see Table 14). If the sample were divided into only three sub-groups, it would show that approximately one-third of the sample was of normal weight (30.7%), one-third overweight (27.3%), and one-third obese (29.4%).

Table 14

Frequency Table of BMI Categories

BMI Category	Frequency	Percent	Valid Percent	Cumulative Percent
< 18.5	118	1.8	2.0	2.0
< 25	2047	30.7	34.4	36.4
< 30	1821	27.3	30.6	67.0

< 40	1613	24.2	27.1	94.1
>= 40	349	5.2	5.9	100.0
Total	5948	89.3	100.0	
System Missing	715	10.7		
Total	6663	100.0		

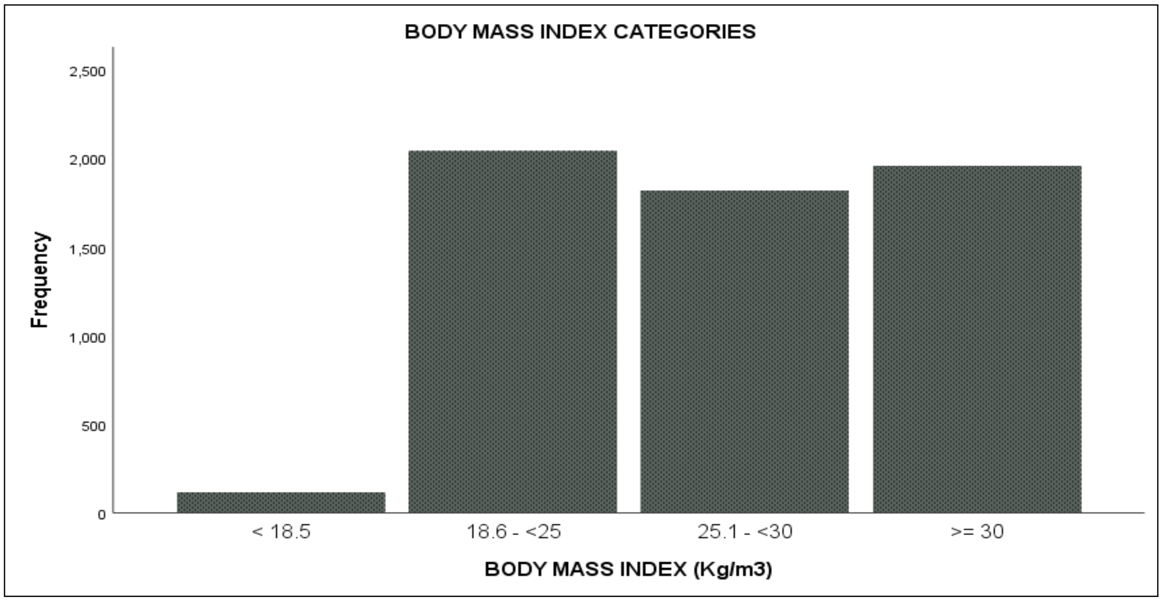


Figure 11. Bar chart of BMI subgroup distribution.

Bivariate Analyses

Pearson Correlation. For the purpose of investigating the relationship between the variable pairs, a Pearson correlation table was generated. This was done with the control variables as they were either continuous or ordinal level (age, income level, and education). The continuous measure of BMI was also included to assess its correlation with these control variables. Based on the correlation coefficient, the strongest correlation was between the control variables Education and Income level (see Table 15), with the coefficient value indicating a positive moderate correlation (r = 0.437). For the other variable pairs, the correlations though statistically significant were very weak, such as the correlation between age and education (r = -.111); education and BMI (r = -.087); and age and income (r = -.051). BMI was also only weakly and negatively correlated with education and income (-.081 and -.129), while its correlation with age was not statistically significant (p = .171).

Table 15

Pearson Correlation Values for Variable Pairs

		Age	Education	Income	BMI
Age	Pearson Correlation	1	-.111	-.051	.018
	Sig. (2-tailed)		.000	.000	.171
Education	Pearson Correlation	-.111	1	.437	-.087
	Sig. (2-tailed)	.000		.000	.000
Income	Pearson Correlation	-.051	.437	1	-.129
	Sig. (2-tailed)	.000	.000		.000
BMI	Pearson Correlation	.018	-.087	-.129	1
	Sig. (2-tailed)	.171	.000	.000	

RACE and EDUCATION. To investigate the relationship between the each of the IVs (Race and Residence), and that of the control variables (age, Education, and Income) several contingency tables, with chi-square analysis, were generated. The cross-tabulation of Race and Education (Table 16) revealed that those belonging to the race subgroups *Others* had the highest percentage of college or technical school graduates (41.7%), followed by *Caucasians* (35.5%), then *African Americans* (27.1%), and lastly *Hispanics* (25.2%). The two top subgroups switched places (but remained at the top) when the measure is at least *some college,* with 78.0% of *Caucasians*, 75.7% of *Others*, 62.1% of *African Americans*, and 54.1% of *Hispanics* meeting that requirement.

Table 16

*Race * Education Contingency Table*

Race	Education completed

	No high school Diploma	High school Diploma	Some College	College/Tech Degree	Row Total
Caucasian	4.1%	27.9%	32.5%	35.5%	100.0%
African American	7.2%	30.7%	35.0%	27.1%	100.0%
Hispanic	11.3%	34.6%	28.9%	25.2%	100.0%
Other	6.1%	18.1%	34.0%	41.7%	100.0%
Total	4.7%	28.0%	32.7%	34.6%	100.0%

Race ***and*** Income. When Race was cross tabulated with Income level (Table 17), the pattern is different from that for Education, despite there being a strong correlation between Income and Education (see Pearson Correlation in Table 15). Here the group with the highest percentage who were earning over $50,000 annually were *Caucasians*, while *Hispanics* are second with 38.6%, and 35.8% for *Others* (see Table 17). Only 26.2% of African Americans were in the highest earning category, and they also had the highest percentage (22.9%) in the lowest earning Income level (below $15,000 annually) compared to only 9.4% of the *Caucasian*s, 13.6% of the *Hispanics*, and 16.1% for *Others.*

Table 17

*Race * Income level Contingency Table*

Race	Income level					
	< $15,000	< $25,000	< $35,000	< $50,000	>= $50,000	Total
Caucasian	9.4%	16.4%	12.6%	15.0%	46.6%	100.0%
African American	22.9%	25.3%	11.4%	14.2%	26.2%	100.0%
Hispanic	13.6%	23.5%	9.8%	14.4%	38.6%	100.0%
Other	16.1%	26.4%	10.6%	11.0%	35.8%	100.0%
Total	11.5%	18.2%	12.3%	14.7%	43.4%	100.0%

Race and Residence: The final cross-tabulation was between the two predictor variables in question, Race and Residence status. This analysis revealed the strongest association between subgroups, as 79.1% of Caucasians owned their own home, while only 48.4% of African Americans were homeowners (see **Error! Reference source not found.**). For the other races, *Hispanics* and *Others*, the percentage of homeowners were higher than that for African Americans, at 58.6% and 59.8% respectively. Along the same lines, the percentage of *Caucasians* who *Rented*, were only 17.2%; but for *African Americans*, the highest among all the races, some 45.9% rented, a little less than half of that subgroup. Approximately one-third (twice the percentage of *Caucasians*) of the other groups, *Hispanics* and *Others*, were renters, 32.5% and 34.6%, respectively, rented.

Table 18

*Race * Residence Status Contingency Table*

Race	Own	Rent	Other	Total
Caucasian	79.1%	17.2%	3.7%	100.0%
African American	48.4%	45.9%	5.7%	100.0%
Hispanic	58.6%	32.5%	8.9%	100.0%
Other	59.8%	34.6%	5.6%	100.0%
Total	74.0%	21.8%	4.2%	100.0%

Chi-squared association between variable pairs. The chi-square analysis of the variable pairs showed moderately strong association between some of the variable pairs. (see Table 19). The two strongest association were between the measures of Income and Residence status (Cramer's V = 0.288) and between Income and Education (V = 0.217). The third strongest relationship was between. Race and Residence (V = 0.177). All the associations between the pairs tested were statistically significant ($p < 0.001$) but the relationship between Race and Education and Race and Income were not as strong, as the V's were 0.071 and 0.117 respectively.

Table 19

Chi-Square Analysis of Variable Pairs

Variable pair	Chi-square	Cramer's V	p-value
Education * Income	1271.99	0.217	.000
Race * Education	99.63	0.071	.000

Race * Income	218.77	0.117	.000
Race * Residence	406.33	0.177	.000
Residence * Education	228.95	0.132	.000
Residence * Income	888.47	0.288	.000

Association to the outcome of obesity. Another set of bivariate analysis was conducted with the IVs and the categorical DV, obesity outcome. In the analysis, the association between the subgroups of the variables across obesity (obese and non-obese) were all statistically significant. The strongest associations were observed in two pairings Obesity-Income and the Obesity-Race, with Cramer's V values*,* 0.120 and 0.113 respectively (20). The association between the other three pairings (Obesity-age, Obesity-Education and Obesity-Residence) were slightly weaker, but still considered moderate, with Cramer's V values of 0.079, 0.097, and 0.072 respectively.

In the tables generated from the Chi-square analysis, the difference in the percentage of obesity in each of the groups could be observed (Table 20). For the Age subgroups, the percentage of persons classified as obese tended to increase going from the youngest (18 to 24) peaking at the 35 to 44 age group, rising from 22.4% to 38.4%. The percentage of obese persons for the remaining three age groups decreased (from 36.5% to 31.8%) as the age-group advanced. This indicated a somewhat inverted u-shaped progression of percentage of obesity with regard to age, as those in the two younger and those in the two older age group having a higher percentage of obesity than those in the two 'middle-aged' groups (See **Error! Reference source not found.**Figure 12).

With the subgroups of levels of Education obtained, obesity was lowest in the most educated (*College/Tech degree*), and highest in the lease educated (*no High School diploma*), 27.0% and 38.8% respectively. It should be noted that the latter of these two subgroups only represented 4.8% of the total sample (Table 20). A similar trend was observed among the Income categories, with the highest annual income (> *$50,000*) bracket having the lowest amount (28.1%) of obese, while the lowest income subgroup (<*$15,000*) having as much as 43.2% of the group obese (Table 20). For the Race subgroups, almost half of the participants who were African American, were also obese (47.1%) compared with less than one-third of the *Caucasian* or *Hispanic* (31.0% and 39.6% respectively). The percentage of obese persons in the *Others* subgroup were also lower than that for *African Americans* (30.3%). And as for Residence status, those who *rented* had a higher percentage of obesity (39.4%) compared to those who *owned* their homes (31.2%) or those who reported some *other* type of living arrangement (29.5%)

Table 20

Contingency Table of Variable Subgroups Association with Obesity

Variable groups		Not obese	Obese	Chi-Square	Kramer' V
Age	18 - 24	78.1%	21.9%	37.55**	0.079
	25 - 34	70.0%	30.0%		
	35 - 44	61.8%	38.2%		
	45 - 54	63.4%	36.6%		
	55 - 64	66.3%	33.7%		
	> 64	68.2%	31.8%		
Education	No high school diploma	61.9%	38.1%	55.89**	0.097
	High school diploma	62.9%	37.1%		
	Some college	64.8%	35.2%		
	College/Tech grad	73.2%	26.8%		
Income	< $15,000	56.1%	43.9%	73.32**	0.120
	< $25,000	61.2%	38.8%		
	< $35,000	63.5%	36.5%		
	< $50,000	63.9%	36.1%		
	>= $50,000	72.1%	27.9%		
Race	Caucasian	69.0%	31.0%	75.07**	0.113
	African American	52.9%	47.1%		
	Hispanic	60.4%	39.6%		
	Other	69.7%	30.3%		
Residence	Own	68.7%	31.3%	30.90**	0.072
	Rent	60.6%	39.4%		
	Other	70.5%	29.5%		
Total		67.0%	33.0%		

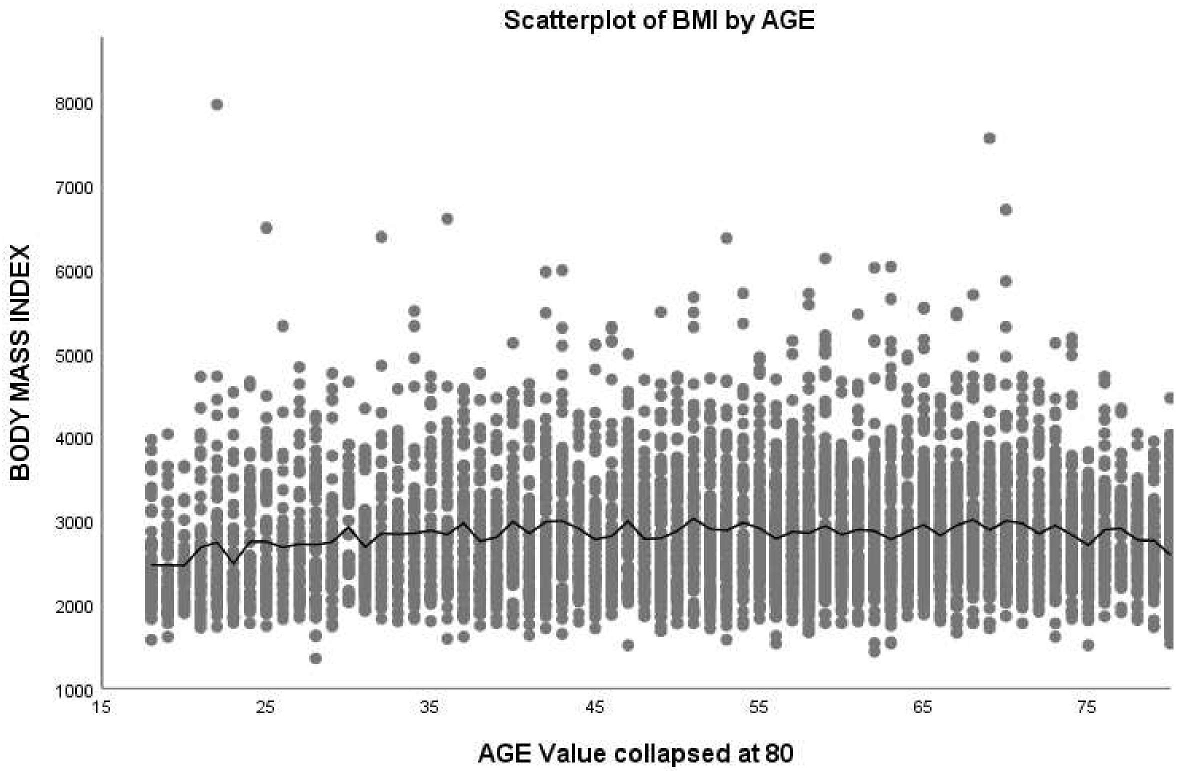


Figure 12. Scatterplot of BMI versus age.

Comparison of means for variables. The final set of bivariate analyses conducted were ANOVA testing to compare the average BMI for the subgroups with that of the others in for each variable. Unlike the Chi-square analysis where all the variables are categorical, the ANOVA and t-Test allows the use of the outcome as a continuous variable and could provide further insight into the relationship between the variables being tested. These tests used the BMI as a continuous variable and compared the size of the actual differences and the statistical significance among the average BMI values. For the Race variable, *African Americans* had a higher average BMI than all other groups, and though the difference was small (1.85, 2.99 and 3.06 kg/m^3 for Hispanics, Caucasians and others respectively) this difference all were statistically significant at a p= 0.001 level (see Table 21). The differences among the other three groups (*Caucasian*, *Hispanic* and *Other*) were not statistically significant.

In comparing the mean BMI for the other subgroups, a similar pattern was observed. For the Income level subgroups, those in the highest income bracket (>= \$50,000) had the lowest average BMI (27.48 kg/m^3), and its difference from the other four subgroups were all statistically significant. In the Education categories, the *college or technical school graduates* had the lowest average BMI (27.30 kg/m^3), and again it was the only difference that was statistically significant. For the Residence status variable, the *Renters* had a higher BMI (29.27 kg/m^3), than both the *Homeowners* (28.00 kg/m^3), and those classified as *Others* (28.09 kg/m^3). The tests indicate that even though the differences among the mean for each of the respective variables were relatively small (1 – 3 kg/m^3), the ones with the highest BMI were statistically significant different from the others. The absence of statistically significant differences in the averages for other respective subgroups could be due to relatively large standard deviation (std. dev. ~ 25% of the values) and the wide ranges in the BMI reported for the subgroups. However, the trend in the average BMI were consistent with the trend observed in the Chi-square/contingency table analysis (Table 20).

Table 21

Table of Mean BMI Value for Variable Subgroups

	N	Mean	Std. Dev.	95% CI for mean		F-statistic
				Lower	Upper	
Race						
Caucasian	4744	27.91	6.51	27.73	28.10	41.26**
African American	701	30.90	7.64	30.33	31.47	
Hispanic	139	29.05	7.05	27.86	30.23	
Other	284	27.84	7.49	26.97	28.72	
Total	5868	28.29	6.79	28.12	28.47	
Income						
< $15,000	570	29.83	8.05	29.17	30.50	21.25**
< $25,000	902	29.23	7.29	28.75	29.70	
< $35,000	622	28.96	7.35	28.39	29.54	
< $50,000	737	28.89	7.09	28.38	29.40	
>= $50,000	2151	27.48	6.00	27.22	27.73	
Total	4982	28.46	6.89	28.27	28.65	
Education						
No high school diploma	286	28.74	7.33	27.89	29.59	22.35**
High school diploma	1650	28.81	6.83	28.48	29.14	
Some college	1932	28.81	7.19	28.49	29.13	
Degree/cert.	2075	27.30	6.15	27.03	27.56	
Total	5943	28.28	6.78	28.11	28.45	
Residence						
Own	4371	28.00	6.33	27.81	28.19	17.67**
Rent	1296	29.27	7.89	28.84	29.70	
Other	244	28.09	7.91	27.09	29.09	

Research Question 1

RQ1: What is the association between the area-level factor residential status (own or rent), and obesity risk among adult African American women after controlling for income, education, and age?

$H_0 1$: There is no association between the area-level factor residential status (own or rent) and obesity risk among adult African American women after controlling for income, education, and age.

H_a1: There is an association between the area-level factor residential status (own or rent) and obesity risk among adult African American women after controlling for income, education, and age.

Building the prediction model. The first step in the multiple logistic regression (MLR) analysis was the test the significance of the three co-factors Age, Income, and Education. To do so a multivariate model was constructed with only these three predictors, and this determined that while Income and Education were significant predictors of Obesity, Age was not, as its p = .891 (Table 22). These results were confirmed by when Age was included as a categorical variable, instead of continuous, in the regression model, as it was still statistically insignificant as p = 0.168 (Table 23). Both Income and Education were significant in either of the models, with p-values less than the α of .05 (p =.000 and p=.007/.010 respectively). As such, only Income and Education were used as control variables in the comprehensive models used to test predictive power of the of two IVs Residence status and Race in answering the research questions.

Table 22

MLR: Preliminary Model 1

	B	S.E.	Wald	df	Sig.	Exp(B)
Age (continuous)	.000	.002	.019	1	.891	1.000
Income level	-.102	.015	44.952	1	.000	.903
Education level	-.098	.036	7.334	1	.007	.906
Constant	.374	.202	3.428	1	.064	1.454

Table 23

MLR: Preliminary Model 2

	B	S.E.	Wald	df	Sig.	Exp(B)
Age (categorical)	.027	.020	1.904	1	.168	1.028
Income level	-.102	.015	45.325	1	.000	.903
Education level	-.094	.036	6.726	1	.010	.910
Constant	.250	.194	1.664	1	.197	1.284

Exploring further in the MLR results for the two significant control variables, Income and Education, revealed negative signs of both B values and an exponent (exp(B) or OR) less than one. Utilizing these two co-factors in the model as categorical variable (instead of as ordinal, semi-continuous variables as in models 1 and 2), the results give better ideas of the nature of the predictive relationship between the subgroups and the obesity outcome (Table 24). Both details are indicative of a negative relationship, implying that a rise in Income or in Education *levels* correlates with reduced odds in the risk of obesity.

For the Education level variable, the highest category of '*college or technical degree*' was used as the reference category. The logistic regression showed that the difference for those with *less than high school* level of Education did not meet significance (representing less than 4% of the sample size). For those who had at least *some sollege* the OR =1.345 and *high school* grads the OR =1.364, indicating that they were 34.5% and 36.4% greater Income odds of obesity risk than the *college/tech* graduates. For the Income level subgroups, the lowest earning subgroup or those with an annual income '< *$15,000*' was used as the reference group in its categorical analysis in the MLR. As the income increased, the odd ratio (OR or Exp(B)) decreased, indicating a reduced likelihood of obesity (20.2%, 25.5%, and 24.2%) relative to the lowest income category. These results reveal that the higher the annual income category, the lower risk of obesity.

Table 24

MLR: Sub-categories of the Control Variables

	B	S.E.	Wald	df	Sig.	Exp(B)
Income (ref: <$15,000)			39.657	4	.000	
<$25,000	-.215	.109	3.858	1	.049	.807
<$35,000	-.295	.120	6.062	1	.014	.745
<$50,000	-.277	.117	5.615	1	.018	.758
>$50,000	-.591	.104	32.507	1	.000	.554

Education (ref: coll/tech deg.)			19.305	3	.000	
Less than high school	.129	.158	.666	1	.414	1.138
High school dip.	.310	.084	13.792	1	.000	1.364
Some college	.296	.077	14.920	1	.000	1.345
Constant	-.491	.106	21.411	1	.000	.612

Research Question 1: Results of MLR. With the statistical significance of the cofactors evaluated, a comprehensive model was built in an attempt to answer the first research question: "What is the association between area-level factor such as residential status (own or rent) and obesity risk among adult *African American* women after controlling for income, Education, and age?" Based on the preliminary analysis, Age was statistically significant and was not included in the comprehensive model. In the comprehensive model, when the data set included participants of all races, Income and Education remained statistically significant, but Residence was not as the $p = 0.098$ (Table 25). In this model, every increase in the Income bracket corresponded to a 8.9% reduced odds of being obese, similarly every move up in Education level correlated with an average reduction of 9.8% in the obesity likelihood.

In the 'all-races' model, the Residence failed to be a statistically significant predictor of obesity status, as the $p > 0.05$ ($p = .098$) but that was not the case in the model built with data separated by race. When the model was generated with a data set selected for *African American* participants only, the odds of obesity for *Renters* was statistically different from that for *Homeowners* (Table 26). In this *African American*-only model, *Renters* had an OR = 1.501, with a p-value of 0.025, indicating that African American *Renters* had a 150.1% greater odds in the risk of obesity, relative to African American *Homeowners*. In this case, *African Americans* who were designated as renters, were found to have a 1.501 more likely to be obese than African Americans who owned their own homes. As such, in reference to the first research question, the null hypothesis can be rejected in favor of the alternative claim that for adult African American women in MI there is a relationship between residential status and obesity. The results indicate that there is an association between the area-level factor residential status (own or rent) and the risk of obesity for adult African American women, after controlling for income and Education.

Table 25

MLR: Comprehensive Model Including All Races

	B	S.E.	Wald	df	Sig.	Exp(B)
Income level	-.093	.016	32.265	1	.000	.911
Education level	-.103	.036	8.106	1	.004	.902
Residence (ref: homeowner)			4.639	2	.098	
Residence (renter)	.126	.077	2.665	1	.103	1.135
Residence (other)	-.207	.176	1.388	1	.239	.813
Constant	.341	.173	3.901	1	.048	1.407

Table 26

MLR: Comprehensive Model African American-Only Data Set

		B	S.E.	Wald	df	Sig.	Exp(B)
African American	Income level	.026	.041	.411	1	.521	1.027
	Education level	-.061	.098	.388	1	.533	.941
	Residence (ref: homeowner)			5.168	2	.075	
	Residence (renter)	.406	.182	4.992	1	.025	1.501
	Residence (other)	.005	.438	.000	1	.990	1.005
	Constant	-.107	.476	.051	1	.822	.898

Research Question 2

RQ2: What is the association between the area-level factor residential status (own or rent) and obesity risk between adult African American and Caucasian women after controlling for income, education, and age?

H$_0$2: There is no association between the area-level factor residential status (own or rent) and obesity risk between adult African American and Caucasian women after controlling for income, education, and age.

H$_a$2: There is an association between the area-level factor residential status (own or rent) and obesity risk between adult African American and Caucasian women after controlling for income, education, and age.

Evaluating the Race Factor. The second research question took a closer look at the Residence status factor across the races. This was done by comparing the reliability of the Residence status variable in predicting the risk of obesity for African American women with that of its reliability in predicting obesity for Caucasian women. Race has been shown to be a major predictor of obesity risk in previous studies (Arroyo-Johnson, & Mincey, 2016; Hales et al., 2017) and it was also confirmed in this data set. When Race was included as an IV in the model with Education and Income, the result indicates that the OR = 1.737 for *African American* women and an OR = 1.563 for *Hispanic* women, when *Caucasian* women were used as the reference group (Table 27). This result suggests that in the state Michigan, *African American* women are 1.737 times more likely, and *Hispanic* women are 1.563 times more likely, to be obese than *Caucasian* women, when controlling for Income and Education.

Research Question 2: Results of MLR. To answer the second research question, the data set was split by categories of the Race variable, and the OR for the Residence factor was compared for *Caucasians* and *African Americans* (See Table 28). The logistic multiple regression model generated, with each race group separately, revealed very important differences in the significance of not just the Residence variable, but in the Income and the Education variables as well. For Caucasian women, as was the case in the all-race model (Table 25), the

Income and Education were predictive ($p < 0.05$), but Residence status was not ($p > 0.05$). For African American women, the reverse was the case, as Income and Education were not predictive (statistically insignificant) and Residence status was the only predictive, i.e. statistically significant ($p < 0.05$) IV. In the *African American*-only model (Table 28), Income and Education were not statistically significant predictors of obesity as their *p*-values were greater than the 0.05 alpha value (*p*-value = .521, and .533 respectively). For *Caucasian* women Residence status was not predictive but Education and Income were (Table 28). Based on these results, the null hypothesis was rejected in favor of the alternative, and it can be claimed that for the adult Michigander women, that there is a difference between the predictive relationship between Residence and the risk of obesity for Caucasian women and African American women. Residence status (own or rent) is a stronger predictor of the risk of obesity for African American women, but it is not predictive for Caucasian women.

Table 27

MLR of the Race Subgroups and Control Variables

	B	**S.E.**	**Wald**	**df**	**Sig.**	**Exp(B)**
Income level	-.084	.016	27.549	1	.000	.919
Education level	-.114	.037	9.338	1	.002	.892
Race (ref: Caucasian)			41.621	3	.000	
Race (African American)	.552	.092	36.063	1	.000	1.737
Race (Hispanic)	.447	.197	5.147	1	.023	1.563
Race (Other)	-.117	.151	.596	1	.440	.890
Constant	.301	.172	3.056	1	.080	1.351

Table 28

MLR: Table of Comprehensive Models Separated by Race

	B	S.E.	Wald	df	Sig.	Exp(B)
Caucasian						
Income level	-.099	.019	26.099	1	.000	.906
Education level	-.108	.042	6.535	1	.011	.898
Residence (ref: Homeowner)			1.400	2	.497	
Residence (Renter)	-.010	.096	.010	1	.919	.990
Residence (Other)	-.248	.210	1.399	1	.237	.780
Constant	.354	.198	3.180	1	.075	1.424
African American						
Income level	.026	.041	.411	1	.521	1.027
Education level	-.061	.098	.388	1	.533	.941
Residence (ref: Homeowner)			5.168	2	.075	
Residence (Renter)	.406	.182	4.992	1	.025	1.501
Residence (Other)	.005	.438	.000	1	.990	1.005
Constant	-.107	.476	.051	1	.822	.898

Summary

Multiple logistic regression analysis was used to analyze the association between the area level factor, residence status, and the risk of obesity in the state of MI. The analysis was based on the 2014- 2016 BRFSS data set and determining if the association was the same for *African American* women as it was for *Caucasian* women was also an objective of the research. The statistical analysis results indicated that Residence status was a statistically significant risk factor for *African American* women, as they were had a 1.501% (p = 0.025) increased risk of obesity relative to *Caucasian* women in the state of MI, when controlling for Education and income. Conversely, the results also indicated that the factor Residence status was not a statistically significant ($p > 0.05$) obesity risk factor for *Caucasian* women. Furthermore, in this data set, while the factors Education level ($p = 0.000$) and Income level ($p = 0.011$) were predictive of obesity for *Caucasian* women, they were not significant predictors of obesity for *African American* women.

Chapter 5: Discussion and Conclusion

This final chapter of the dissertation summarizes and interprets the results of the analyses performed with respect to the conceptual framework that guided the research design. The summary section includes an interpretation of both the descriptive and inferential statistics in light of previous research findings and concludes with suggestions for future investigations related to these findings. The section outlines recommendations and proposed objectives for these future investigations related to the relationship between obesity and area-level risk factors. The chapter ends with a general conclusion for the study, which serves as a synopsis of all five chapters and an abstract statement for the entire research project.

Interpretation of Results

Interpretation of the Descriptive Statistics

Distribution of categories for the variables. The first step in the risk factor study included a descriptive analysis of all the variables chosen from the MiBRFSS. The control variables were age, Education, and income; the IVs were race and residence status; and the outcome variable was obesity status. The distribution of gender was not considered in this study, as the selected data set included only female respondents. Prior research has shown that gender is a major risk factor for obesity (Fradkin, Wallander, Elliott, Cuccaro, & Schuster, 2015; Hallam, Boswell, DeVito, & Kober, 2016; Mühlberg, Mathar, Villringer, Horstmann, & Neumann, 2016), with women having a higher prevalence than men, particularly before the age of 65 (Breland et al. 2017). Based on the role of gender in obesity prevalence, I focused solely on female respondents. The objective was to zero in on the target population (African American women), which is also the group least represented, and conduct research on obesity and the obesity-related area-level risk factor, namely residence status.

The first control variable assessed descriptively was age, which was eventually excluded from the statistical analysis as it proved statistically insignificant. The age variable was approximately normally distributed despite the ‘collapsed at 80’ category. This collapsing at the upper extreme did not affect the results of the inferential analysis as proved to be insignificantly predictive of the outcome in question, whether included as a continuous variable or as a categorical variable. The distribution, although normal, had a high average (55 years); those respondents under 45 years made up only 25.7% of the total population, compared with respondents over 45 years (74.3%); this may have introduced an age-selection bias (see Table 16). Consequently, the results should be interpreted as relating more to a middle-aged to older group than that of a younger age group.

The other two control variables, Income level and Education level, were found to be slightly biased by somewhat unequal distribution in the sample data set. Given that these two variables are considered measures of SES (Fitzpatrick et al., 2015; Singh, Sharma, & Nagesh, 2017), the descriptive analysis indicated that this data set was drawn from a slightly higher SES bracket. According to official federal poverty guidelines, an average-sized family of four is considered above the poverty level if the household income is over $26,000 annually (U.S. Department of Health and Human Services, 2017). In this data set, more than 60% were earning over $25,000, more than half of which (35.0% of the total) were earning nearly twice that amount annually (see Table 17). Given that no information on actual family size corresponding to these income values, it is difficult to correlate this data directly with SES. Additionally, the income data were collected and reported categorically, so determination of mean and other measures of central tendency was not possible. Similarly, as in the case of income, the Education level variable was also reported as categorically, but here the descriptive analysis reflected a closer resemblance to the general population, with each category (high school graduate, some college, and college graduate) representing approximately one third (U.S. Census Bureau, 2016).

The distribution of the race variable was important to the internal validity of this study for a number of reasons. First, race has been shown to be one of the strongest risk factors related to obesity, as African Americans and Hispanic Americans consistently have higher prevalence of obesity than Caucasian Americans or Asian Americans do (Bell et al., 2019; Hales et al., 2017; Powell et al., 2016). Secondly, race is the variable by which the data set was stratified prior to conducting the statistical analyses to generate the answers to the research questions. In this MiBRFSS sample, the percentage of African Americans (and the ratio African Americans:Caucasians) is comparative to that reported in the official census numbers for the state of Michigan (African Americans: 13.9 vs. 11.7% and Caucasians: 79.3% vs. 79.6% for MiBRFSS vs. U.S. Census), and as such, the validity of the results was retained (U.S. Census Bureau, 2016).

The IV of interest, residence status, was reported with only three categories: homeowner, renter, and other. This basic classification simplified the interpretation of the MLR analysis, but living conditions are usually much more nuanced and can be complicated by the time factor involved. For a better understanding of the impact of factors of residence status, the question of "How long has the condition existed?" is important. Because this was a cross-sectional data set, no information on time was collected and therefore could not be included in the analysis. The distribution of the residence status variable was approximately the same as that for national and state values, with approximately 64.5% nationally and 71.2% of the Michigander population being reported as homeowners (U.S. Census, 2016). In this MiBRFSS data set, 73.9% of the women were homeowners, and 21.9% were renters, indicating a similar 3:1 bias toward homeownership as seen in the official census data.

The final descriptive analysis was that for the variable used to generate the outcome factor BMI on which obesity status was based. The BMI values, though slightly right skewed, were approximately normally distributed and comparable to the general population (see Figure 9). Like in the U.S. population at large, in the MiBRFSS, one third of the sample was considered normal weight, another one third was considered overweight but not obese, and the other one third was obese (Fryar, Carroll, & Ogden, 2018). A small but significant percentage were morbidly obese (5.9%); some of these were among the younger subjects (ages 18–24), which possibly indicated cases other than chronic disease. If the cause was genetic obesity, these individuals should have been considered as outliers and excluded from the data set. However, as no clinical or longitudinal information was provided, it was not possible to make such determinations and no obese persons were excluded from the analysis. Including cases of obesity that may be more congenital in nature may have compromised the reliability of the results.

Interpretation of the descriptive statistics result. The correlation analysis revealed connections between the variables, some of which were seen to be relatively strong correlations. As was expected, the strongest correlation was between the ordinally measured variables related to SES, income and Education levels. According to the Pearson coefficient (0.437), the implication was that the higher the level of Education attained, the higher the annual income earned. The Chi-square analysis also confirmed the relationship between income and Education, but it revealed that the relationship between residence and income was the stronger of the two, with Cramer’s V values of 0.217 and 0.288, respectively (see Table 19). Again, the results indicated that those who were more educated were more likely to be in a higher income bracket, and those who earned more were more likely than not to own their own home.

Interestingly, the aforementioned strength of association between the variables were not consistent across the different race groups. For example, even though African American women had almost the same percentage of those with at least some college Education as Caucasians, 62.1% and 68.0% respectively (see Table 16), only 26.2% of African Americans, compared with 46.6% of Caucasians were earning over $50,000 annually (see Table 17). Furthermore, while 79.1% of Caucasians were homeowners, only 48.4% of African Americans reported the same residential status. This coincides with the Chi-square analysis indicating a moderately strong association between the *race* groups and the *residential* categories, as *homeownership* was not equally distributed across the races, with the percentage of *Caucasian* homeowners being almost twice that the percentage of *African American* homeowners. These differences in the measure of the association among the variables reflected the inequality experienced by African Americans in general, as the benefits of a higher Education did not materialize into higher incomes or into better living conditions for African Americans as they did for Caucasians. This points to the need for further analysis into such incongruencies in the association among these IVs and the possible confounding effect this may have as it relates to the health outcomes in general and obesity outcomes specifically.

Association of the independent variable with obesity. The bivariate analyses also provided insight into the strength of the association of each of the IVs with the outcome variable of obesity. In the contingency table analysis (Table 20) the variable with the strongest association with obesity was INCOME (Cramer's V= 0.120), followed by RACE (Cramer's V = 0.113), which was subsequently confirmed in the MLR analysis. This is noteworthy given that the disparity in the INCOME distribution, for Caucasians compared to African Americans, despite the EDUCATION levels being the same. Again, these results demonstrate the need for more in-depth study into the role of these control variables across each race, separately. This inequality was further emphasized in the interpretation of the MLR in inferential statistics results in discussed next section.

The association between that of INCOME and of EDUCATION each with that of an obesity outcome were congruent and reflected the protective factor associated with the two variables (See Table 20). The results showed that the prevalence of obesity decreased with each rise in income or in Educational levels, with the poorest (lowest income) and the least educated (lowest Educational level) having the highest proportion of obese persons. Unfortunately, as the stratified MLR results would show, these benefits were limited only to Caucasian women and were not being experienced by African American women. As part of the supplementary analysis (results not shown), cross-tabulation revealed that for Caucasian women living in a household earning more than $50,000 a year, only 26.6% were obese, while for African American women with the same earnings, some 47.7% were obese. This is yet another instance of the racial inequality, showing that the benefits of an increased income (as well as Education) were not being experienced by African American women as they were for their Caucasian contemporaries.

The relationship between AGE and the risk of obesity was not clear from the data analysis conducted here. As the scatterplot of BMI versus AGE (Figure 12) indicated the trendline paralleled the x-axis, although slightly u-shaped with dips at either end representing the marginally lower BMI for the youngest and oldest subjects. The effectively straight trendline is contrasted with the results of studies decades earlier, where the trendlines had a positive slope, as

BMI would increase with age. The straighter trendline tells of the changes in the prevalence of BMI with the age groups, as the incidence of obesity increasing more rapidly in the younger persons than those in an older age group. In the last several decades the BMI among all age groups have been seen significant increases, and the percentage of those considered obese rose from approximately 11% in the early 1960s to almost 33% by early the 2010s (National Academies of Sciences, Engineering, and Medicine, 2016). The trend research has shown that obesity has almost tripled for the general population over the last half-a-century, and as the findings in this research confirms, there is a loss of the protection of youth in staving off obesity and all of its related complications (See Figure 13).

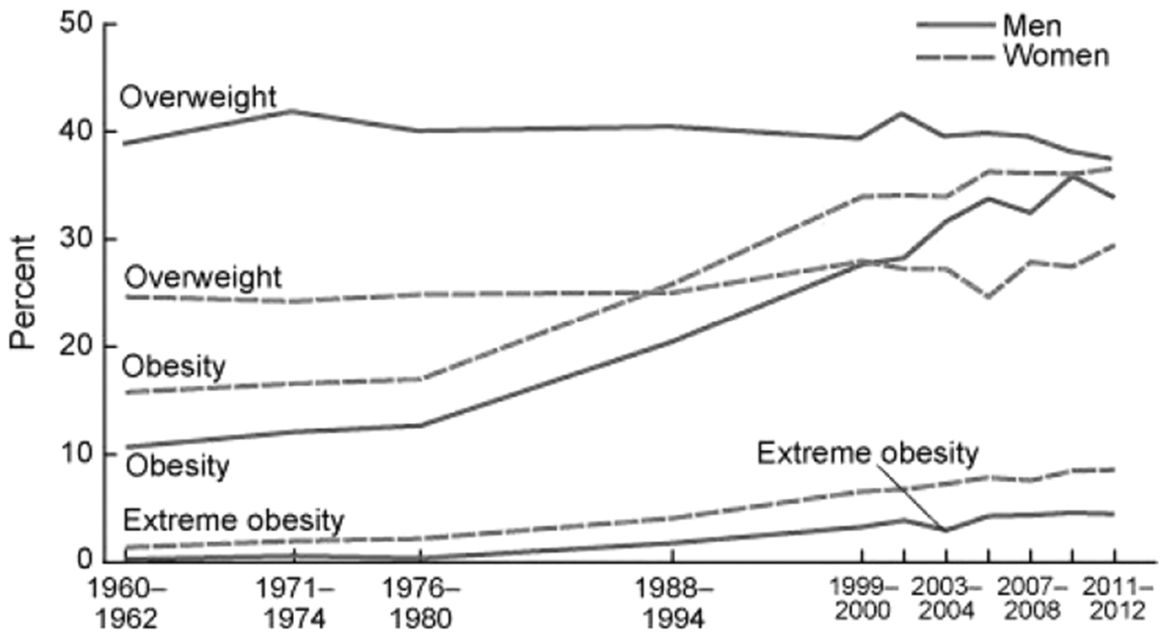


Figure 13. Trend in obesity prevalence, last 50 years. (National Academies of Sciences, Engineering, and Medicine, 2016)

Interpretation of the Inferential Statistics Results

The main objective of this study research was to determine the strength of the association between the area level factor- RESIDENCE STATUS, and obesity for African American women, and to determine how the strength of this relationship between these two factors compare with that for Caucasian women. In the multiple logistic regression (MLR) analysis of conducted using only data from the African American subjects determined that there was in fact a very strong relationship between residential status and the risk of obesity for the African American women living in Michigan. According to the results (See Table 26), African American *renters* were 1.5 times more likely to be obese than African American *homeowners* (OR = 1.501, $p = 0.025$). Furthermore, not only was RESIDENCE status shown to be the strongest of the risk factors assessed, it also reduced the impact of INCOME and EDUCATION on obesity risk to insignificant (Table 26), when included in the analysis. So, according to this data set, for African American women living in Michigan, nothing has a greater impact on their likelihood of developing obesity than does their residence status, when controlling for income and Education.

When the MLR was conducted using the entire data set (all races of women included) the results indicated that RESIDENCE STATUS was *not* a statistically significant risk factor for obesity. In this case, only INCOME (OR = .919, $p = .000$) and EDUCATION (OR = .892, $p = .002$) were predictive of an obesity outcome, and these results this held true when the data set only contained Caucasian subjects (See Tables 24 and 25). Therefore, the conclusion is that for Caucasian women living in Michigan, RESIDENCE STATUS is not a risk factor, as only EDUCATION and INCOME are significant obesity risk factors. For Caucasian women, it didn't matter what your residential status was, all that mattered were their Income level and their EDUCATION level as far as the risk of becoming obese was concerned.

The findings from this research are novel to the field of obesity risk research and provide important insights for further research. As with previous studies, the role of RACE played a significant part in obesity prevalence in the U.S. and the results here confirmed RACE is a significant factor, as African Americans and Hispanics are 1.737 and 1.563 times (respectively) more likely to be obese than Caucasians (see Table 24). What has not been published before, is the role of each of the risk factors (INCOME, EDUCATION, and RESIDENCE) when the races are evaluated separately. This exclusive analysis has revealed very critical differences and invaluable insight into the process by which race may be influencing the risk of obesity. There is no confirmation of causal relationship as this is observational data, but it does highlight the need for further research, specifically into the strength of each risk factor is predicting the obesity for each race group, separately.

Interpretation Relative to the Conceptual Framework

The design for this research was based on SEM and SCT, and both theories emphasize the impact of social factors on health outcomes. Many clinical and medical research endeavors have focused on the biological/etiological development of obesity, while the public health studies have focused on the characteristic risk factors such as race, gender, age, income, and Education. Few studies, however, have looked at the sociodemographic factors involved in the risk for chronic diseases. What this present research has shown is that for particular people groups (racial or otherwise), certain sociodemographic can be very strong predictors of health outcomes for one group while not being predictive for others.

With the SEM, the emphasis is placed on environmental factors over the personal and interpersonal ones. This study used the personal factors (income and Education) as controls when evaluating the strength of the impact of the environmental factor of residence status. The difference between living in a house that you own, more likely than not, involves living in an area that provides socio-physical features that foster better health. Houses, as opposed to apartment buildings, are more often located in areas with community parks and walking trails and other opportunities for physical activities. They are also more likely to have access to grocery stores where healthier food options are more readily available. And so, while it is not feasible to measure all these aspects of the socio-physical environment, factors such as *residence status* can be used as general representation to assess their role in health outcomes.

The SCT focused on the interpersonal factors such as normative beliefs, cognition, self-regulation, self-efficacy, and motivation. Using SCT allows for consideration of the influence of cultural forces on these personal factors which in turn impact a person's health perceptions, their behavior, and their health outcomes. As social beings, ideas about what is healthy as well as what is within one's power to determine health status, depends on what is regularly promoted consciously and subconsciously, in one's community. Views on ideal weight and obesity status vary from one social group to another, and it is the assumption of this study, based on the SCT theory, that those living in the homes they own, compared to those living in an apartment building, may be more likely to be exposed to different concepts of weight and obesity status. Therefore, the use of residential status as a predictor variable is one of the ways to assess the roles of socio-cognitive factors in obesity outcome. Though the study data did not distinguish beyond the general (homeownership and renting), the distinction between these two did provide adequate distinction to determine that there were statistically significant differences.

What SCT and SEM both point to is that there are important sociodemographic factors and that these factors are part of the racial disparity involved in health outcomes, and it is important to account for this in related research. As Dr. Williams, a renowned social scientist at Harvard University, research has proven, there is a complicated interplay between race and physical and mental health in the United States (Cuevas et al., 2020; Van Dyke et al., 2019; Williams, Lawrence, Davis, & Vu, 2019). Research has shown some of the specific ways in which racial discrimination- manifested through 'implicit biases, residential segregation, and negative stereotyping'- all profoundly drive racial disparity and increase the likelihood of chronic diseases in African American and other disenfranchised minorities (Williams, & Mohammed, 2013). Findings like those reported by Dr. Williams and his colleagues support those in this study that emphasize the need for public health research to not only have greater representation from these minority groups but to also include research design that specifically focuses of each minority group as a separate entity.

Limitations

There were several limitations involved in the data treatment and analysis that should be considered in having an impact on the research results and its interpretation. Firstly, although MLR allows for the inclusion of several IVs to determine their combined impact on outcome, it is not always ideal for certain disease outcome. In the case of obesity, unlike cardiovascular disease or kidney disease, the 'diagnosis' is based solely on a somewhat arbitrarily chosen BMI value and not a clinical determination by a medical professional. The fact that obesity is based on a BMI value and that its diagnosis reduces a continuous variable to binomial variable, results in a significant loss of information. In some cases, using the information as a continuous variable and conducting a linear regression or an ANOVA analysis could prove to be more accurate and more informative.

When it comes to deciphering the intricacies of obesity and its multifaceted etiology, a qualitative study may be more effective. For example, in this study, no account was taken as to the co-existence of other diseases or the time sequence involved in the disease development, i.e. how long had the individual been obese? Similarly, no account was taken as to the time element involved in the predictor variables, namely the individual's RESIDENCE STATUS, i.e. how long had they owned their home? The absence of this type of information in cross-sectional data limits the determination to only correlational estimation. In fact, there have been studies that point to the bidirectional nature of the relationship between factors of socioeconomics and other related to obesity risk. These factors can only be assessed causally in path analysis of prospective data or thorough the analysis of data collected from randomized controlled clinical experiments.

Another major limiting factor to this study is the self-reporting nature of all the BRFSS data sets. The data collected were based solely on what the researchers were told by the subjects, and as with other self-reporting data, there is always the possibility of recall biases and inaccuracies, especially as it relates to weight and other health factors. The data collected by the BRFSS has proven to be an invaluable resource for assessing the health of the U. S. citizenry and measuring the progress of health interventions implemented in the various states across the nation. However, like other self-reported data the possibility of bias introduced because of social desirability, selective recall or simple erroneous determination of the responses, must be considered (Althubaiti, 2016). That is one of the reasons why, the results of cross-sectional data analysis such as this should serve as the basis for further experimental research inquiry, before definite determinations are made, and interventions are developed.

Implications for Additional Research

One of the obvious areas for recommendation for future research relates the distribution of the races in the sample data set. Here, as was the case with so many previous studies, the representation of African American subjects was inadequate. Even though the distribution closely reflected that of the general population, the results clearly show that these inadequacies can cause an imbalance and can generate misleading results, especially when the data set is evaluated as a whole. When the percentage of the minorities in the data set is low, the results can be dominated by the results for Caucasian Americans. And these results, as have been proven in this study, can not only be an inaccurate representation of the actual results, but they can also portray results that are the contrary to what is the case for these underrepresented groups.

Other areas of possible improvement for future research that focuses on the internal validity of the results has to do with the process of stratification. There are a number of ways that data like this can be stratified, including separating by and comparing the results for different age groups (young, middle-aged and older subjects), Also, comparing results for different income earning classification (low-income vs high-income); for different Educational levels attained (high-school graduates vs. college graduates); or for other races (including Hispanics, Asians, etc.). Just as the 'African American/Caucasian' stratification proved to be extremely insightful into the differences in the risk factor relationship, so too could other comparisons lead to improved understanding into the nature of the obesity disparity problem.

The results of this study, though meaningful, can only be applied to the women in the state Michigan, and as such in spite of the insight, is limited in its scope. What the results do point to, is the need to repeat this type of research for the women of other states and determine if they hold true. And even for the state of Michigan, before the results can be used as the basis for health intervention planning or even policy development, there is the need for additional more research. The BRFSS data provide an excellent overview, but for a deeper understanding, but more thorough data collection process is needed, one that provides more reliable, precise medical information about each of the study subjects. Future studies should also be retrospective or prospective in nature to account for the time factor as it relates to both the independent and DVs and they should include official medical records as well as verifiable income and Education documentation.

Implications for Positive Social Change

Obesity is a leading cause of disease and death and it disproportionately affects female members of the African American race in this country. There has been extensive research conducted to understand obesity's etiology in general, with little focus on the cause of the racial disparity. The research has been constrained by various biases in the makeup of the data and its limited representation from these high-risk groups. What this study has uncovered is that, when it comes to obesity, there are key differences in the role of risk factors for African American women, compared to Caucasian women, namely housing status. Important socioeconomic differences such as this can have major individual and communal implications for social change.

The social change propositions that can be applied in a general manner refers to the public health leaders, the research community, and the policy makers and stakeholders. Firstly, it appears that the results of previous research should be regarded with caution, as the imbalance of race group could have affected the reliability of the findings. This study emphasizes the need to have a more balanced representation (or a separation) in the sample and the research design. Secondly, policies that failed to incorporate the effect of societal factors in their development and implementation, specifically as it applies to African American women, may have missed the mark and therefore rendered less effective. The need is now for updating and revising said policies, procedures and guidelines relating to the dealing with obesity in the African American community, and other minority groups. Thirdly, healthcare professionals and others on the frontline need to alter the way they screen the population for obesity. Risk assessment tools, as well as public health planning and promotion, should be made to reflect evidence-based findings to ensure their superior effectiveness in identifying those at risk and treating those who are already diagnosed.

There is another area of positive social change and this involves creating awareness at the level of the individual. Being educated about the socio-economic factors involved in the risk of developing obesity can be very empowering for those involved. Such awareness allows for an increase their sense of autonomy and self-efficacy as they do battle to treat or prevent the disease for themselves and their families. Those who are obese and those who are at risk for obesity may now be encouraged to seek out counselling and support that addresses the psychosocial aspect of the disease and thereby be armed with tools that will make their struggle more manageable and more likely to lead to solutions. Knowing that one’s lived-area factor has an impact on one’s risk for obesity emphasizes the need to address those things that are modifiable, i.e. self-care, lifestyle changes, and attitude, even in the absence of socioeconomic autonomy.

Conclusion

The chronic disease of obesity places a major financial burden on the public health care system, and it carries a wide range of physical, mental and emotional dangers to those affected. While previous research has indicated the multifaceted nature of this disease, there is still much to be uncovered and this research sought to fill in area of the existing gap. The results of this study confirmed the role of SES characteristics such as *Income level* and *Educational level* in the risk of developing obesity. Additionally, specific to this data set, the variable *age* was not found to be a statistically significant predictor of an obesity outcome. What the research has highlighted, that has not been previously reported, is the role of the area-level factors, specifically *residence status*, as a major risk factor, stronger than income and Education, for African American (but not for Caucasian) women living in Michigan. These findings provide crucial information relevant to the health intervention efforts needed in responding to the epidemic of obesity and the racial disparity with which it presents. However, based on the limitations mentioned, further research is needed before any use or generalization of these findings can be made.

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