

2018

Examining Health Disparities and Childhood Obesity in Florida and Georgia

Jennifer Wesley
Walden University

Follow this and additional works at: <https://scholarworks.waldenu.edu/dissertations>

 Part of the [Public Health Education and Promotion Commons](#)

This Dissertation is brought to you for free and open access by the Walden Dissertations and Doctoral Studies Collection at ScholarWorks. It has been accepted for inclusion in Walden Dissertations and Doctoral Studies by an authorized administrator of ScholarWorks. For more information, please contact ScholarWorks@waldenu.edu.

Walden University

College of Health Sciences

This is to certify that the doctoral study by

Jennifer Surone Wesley

has been found to be complete and satisfactory in all respects,
and that any and all revisions required by
the review committee have been made.

Review Committee

Dr. Manoj Sharma, Committee Chairperson, Public Health Faculty

Dr. Xianbin Li, Committee Member, Public Health Faculty

Dr. Simone Salandy, University Reviewer, Public Health Faculty

Chief Academic Officer

Eric Riedel, Ph.D.

Walden University

2017

Abstract

Examining Health Disparities and Childhood Obesity in Florida and Georgia

By

Jennifer Surone Wesley

MPH, Georgia Southern University, 2003

BS, Georgia Southern University, 2000

AS, South Georgia College, 1998

Doctoral Study Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Public Health

Walden University

November 2017

Abstract

Childhood obesity is a major issue in the United States. The rates of obesity vary among racial and ethnic groups in the U.S. South. The purpose of this quantitative cross-sectional study was to investigate significant state health disparities differences in childhood obesity in the South region between Florida and Georgia. To steer this study, the social cognitive theory was used. The associations between neighborhood safety and support, physical activity, family health and activities on body mass index were examined in this study. Data was obtained from the National Survey of Children's Health 2011-2012 on 1,688 children aged 10-17 years residing in Florida and Georgia. Logistic regression models showed children in Georgia were 1.4 times more likely to be overweight/obese than children in Florida. Significant differences were found in Florida and Georgia for neighborhood safety and support, physical activity, and family health and activities with evidence to reject the null hypothesis for each state separately. There was no evidence to reject significant differences between Florida and Georgia on sociodemographics. Public health professionals could benefit from researchers studying the causes of racial/ethnic and socioeconomic health disparities in childhood obesity. Thus, professionals could use these results to develop programs targeted at minority populations at increased risk. Positive social change implications of these finding could provide more insight on childhood obesity in the South, where more research is vital. This could be achieved through creating state-specific policies, raising awareness, and implementing prevention programs to decrease childhood obesity.

Examining Health Disparities and Childhood Obesity in Florida and Georgia

by

Jennifer Surone Wesley

MPH, Georgia Southern University, 2003

BS, Georgia Southern University, 2000

AS, South Georgia College, 1998

Doctoral Study Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Public Health

Walden University

November 2017

Acknowledgments

First, I would like to thank God, my parents (William & Betty), brothers, and sisters for supporting me during this doctoral journey. Your unconditional love, faith, and constant prayers meant a lot to me. I hope I have made all of you proud of me. A very special thanks to Jennifer Hicks, Crystal Russell, Sharra Triplett, Emily Spivey, Lisa Jones, Ced Haney, Thomas Bangs, and friends for your calls, encouragement, and continuous support. I appreciate all of you for listening to me when I called to vent about my dissertation. Also, I would like to thank my ATC family (Sharon Dewberry-Outlaw, Peggy Williams, Charles Jones, and Dr. Ojore) for your support and being there for me. I am blessed to have all of you in my life. Much love to all of you.

Also, much thanks to my committee chair, Dr. Sharma and committee member, Dr. Li for your assistance. I truly appreciated all your comments, questions, and expertise in content and methodology. Your feedback, guidance, and encouragement with my dissertation helped made all this possible. Thanks for assisting me with accomplishing my dream and now pursue my passion in public health.

Table of Contents

Section 1: Foundation of the Study and Literature Review	1
Introduction.....	1
Problem Statement.....	3
Purpose of the Study.....	5
Research Question(s) and Hypotheses.....	6
Theoretical Foundation of the Study.....	7
Nature of the Study.....	9
Literature Search Strategy.....	10
Literature Review Related to Key Variables and/or Concepts.....	11
Definitions.....	31
Assumptions.....	32
Scope and Delimitations	32
Significance, Summary, and Conclusions	33
Section 2: Research Design and Data Collection	36
Introduction.....	36
Research Design and Rationale	36
Methodology.....	38
Population	38
Sampling and Procedures Used to collect Data	39
Instrumentation and Operationalization of Constructs	44
Research Question(s) and Hypotheses.....	56

Threats to Validity	58
Summary	61
Section 3: Presentation of the Results and Findings Section	62
Introduction	62
Research Question(s) and Hypotheses	62
Data Collection of Secondary Data Set	63
Results	65
Descriptive statistics	65
Statistical assumptions	75
Statistical analysis	75
Research Question(s) and Hypotheses	76
Summary	116
Introduction	119
Interpretation of the Findings	122
Limitations of the Study	128
Recommendations	128
Implications for Professional Practice and Social Change	130
Conclusion	131
References	133

List of Tables

Table 1. Descriptive Statistics of Sample Population.....	66
Table 2. Descriptive Statistics for Neighborhood Safety and Support - Social Capital.....	67
Table 3. Descriptive Statistics for Neighborhood Safety and Support - Perceived Safety.....	68
Table 4. Descriptive Statistics for Neighborhood Safety and Support - Neighborhood Conditions.....	69
Table 5. Descriptive Statistics for Neighborhood safety and support - Neighborhood Amenities.....	70
Table 6. Descriptive Statistics for Physical Activity.....	71
Table 7. Descriptive Statistics for Family Health and Activities - Family eats meals together.....	72
Table 8. Descriptive Statistics for Family Health and Activities - Time spent watching TV.....	72
Table 9. Descriptive Statistics for Family Health and Activities - Time spent with electronics.....	73
Table 10. Descriptive Statistics for Family Health and Activities - Electronics in the bedroom.....	74
Table 11. Descriptive Statistics for Family Health and Activities - Time spent reading.....	74

Table 12. Coefficients for Measuring Multicollinearity for Neighborhood Safety and Support.....	78
Table 13. Omnibus Tests of Model Coefficients of Block 1 for Neighborhood Safety and Support.....	80
Table 14. Model Summary of Block 1 for Neighborhood Safety and Support.....	80
Table 15. Omnibus Tests of Model Coefficients of Block 2 for Neighborhood Safety and Support.....	81
Table 16. Model Summary of Block 2 for Neighborhood Safety and Support.....	82
Table 17. Logistic Regression Predicting Likelihood of being Overweight/Obese based on Neighborhood Safety and Support.....	83
Table 18. Omnibus Tests of Model Coefficients of Neighborhood Safety and Support for Georgia.....	84
Table 19. Model Summary of Neighborhood Safety and Support for Georgia.....	85
Table 20. Logistic Regression Predicting Likelihood of being Overweight/Obese in Georgia.....	85
Table 21. Omnibus Tests of Model Coefficients of Neighborhood Safety and Support for Florida.....	87
Table 22. Model Summary of Neighborhood Safety and Support for Florida.....	87
Table 23. Logistic Regression Predicting Likelihood of being Overweight/Obese in Florida.....	88
Table 24. Omnibus Tests of Model Coefficients of Block 1 for Physical Activity.....	90

Table 25. Model Summary of Block 1 for Physical Activity.....	90
Table 26. Omnibus Tests of Model Coefficients of Block 2 for Physical Activity....	90
Table 27. Model Summary of Block 2 for Physical Activity.....	91
Table 28. Logistic Regression Predicting Likelihood of being Overweight/Obese....	91
Table 29. Omnibus Tests of Model Coefficients of Physical Activity for Georgia....	92
Table 30. Model Summary of Physical Activity for Georgia.....	92
Table 31. Logistic Regression Predicting Likelihood of being Overweight/Obese in Georgia.....	93
Table 32. Omnibus Tests of Model Coefficients of Physical Activity for Florida...	94
Table 33. Model Summary of Physical Activity for Florida.....	94
Table 34. Logistic Regression Predicting Likelihood of being Overweight/Obese in Florida.....	95
Table 35. Coefficients for Measuring Multicollinearity for Family Health and Activities.....	98
Table 36. Omnibus Tests of Model Coefficients of Block 1 for Family Health and Activities.....	99
Table 37. Model Summary of Block 1 for Family Health and Activities.....	99
Table 38. Omnibus Tests of Model Coefficients of Block 2 for Family Health and Activities.....	100
Table 39. Model Summary of Block 2 for Family Health and Activities.....	100
Table 40. Logistic Regression Predicting Likelihood of being Overweight/Obese.	102

Table 41. Omnibus Tests of Model Coefficients of Family Health and Activities for Georgia.....	103
Table 42. Model Summary of Family Health and Activities for Georgia.....	104
Table 43. Logistic Regression Predicting Likelihood of being Overweight/Obese in Georgia.....	104
Table 44. Omnibus Tests of Model Coefficients of Family Health and Activities for Florida.....	106
Table 45. Model Summary of Family Health and Activities for Florida.....	106
Table 46. Logistic Regression Predicting Likelihood of being Overweight/Obese in Florida.....	107
Table 47. Coefficients for Measuring Multicollinearity for Sociodemographic.....	110
Table 48. Omnibus Tests of Model Coefficients of Block 1 for Sociodemographic....	111
Table 49. Model Summary of Block 1 for Sociodemographic.....	111
Table 50. Omnibus Tests of Model Coefficients of Block 2 for Sociodemographic...	112
Table 51. Model Summary of Block 2 for Sociodemographic.....	112
Table 52. Logistic Regression Predicting Likelihood of being Overweight/Obese.....	115

Section 1: Foundation of the Study and Literature Review

Introduction

In the United States, childhood obesity is an epidemic, and it is a multifaceted problem. The rates of childhood obesity have increased among racial/ethnic groups, on all socioeconomic levels, and various regions of the United States (Miyazaki & Stack, 2014; Parikka et al., 2015). Obese children are more likely to develop chronic health conditions such as cancer and stroke later in adulthood (Kahan & McKenzie, 2015). Approximately 34% of adolescents aged 12 to 19 living in the United States were either overweight or obese during 2007-2008 (Crespi, Wang, Seto, Mare, & Gee, 2015). In several countries, the occurrence of childhood obesity is more than 25% (Crespi et al., 2015). For example, in Europe as well as other developed countries, a higher percentage of overweight children come from families with lower socioeconomic status (Parikka et al., 2015). In the United States, nearly one-third of children and adolescents ages 6 to 19 are overweight or obese; whereas one in six children and adolescents ages 6 to 19 are obese based on data from the National Health and Nutrition Examination Survey (NHANES), 2009-2010 (National Institutes of Health, [NIH], 2012).

When the body has an energy imbalance it leads to overweightness and obesity. This imbalance implies the body is consuming more calories and burning less energy (NIH, 2012). Thus, for children to have energy balance, the energy being used and food intake should support growth and not contribute to extra weight gain (NIH, 2012). Several factors contribute to energy imbalance and childhood obesity such as genetics, physical activity, parenting style, sedentary habits, where you live, income, attitudes, and

environmental factors (NIH, 2012; Parikka et al., 2015). A tool regularly used to calculate overweightness and obesity in adults and children is (BMI) or body mass index (NIH, 2012). To combat childhood obesity, it is imperative that these factors are examined.

In the United States, health disparities in childhood obesity exist in the southern region. Thus, childhood obesity rates in the southern states are higher compared to other states (Trust for America's Health, 2014). The prevalence of obesity is greater in the South between racial and ethnic minorities, children living in poorer socioeconomic regions, and rural areas (Holt et al., 2011). Furthermore, there is a need to address geographical disparities in the South since; there is limited research in this region (Meyers, Slack, Martin, Broyles, & Heymsfield, 2015). Florida and Georgia are two states in the South at risk for childhood obesity. Based on data from the National Survey of Children's Health 2011/2012, about 27.5% of children ages 10 to 17 in Florida and 35% in Georgia are overweight or obese. Nationwide, about 31.3% are overweight or obese with a BMI greater at or greater than the 85th percentile (Data Resource Center for Child & Adolescent Health, [DRC], 2012).

The prevalence of childhood obesity in Georgia among 10 to 17 year olds is 16.5% (University of Georgia, n.d.). Georgia is ranked 18th with the highest adult obesity rates at or above 30% in the United States (University of Georgia, n.d.). Florida is ranked 39th for overweight or obese children and has the worst race disparity ratio in the United States (National Institute for Children's Health Quality [NICHQ], n.d.). Since obese children and adults have more risk of acquiring chronic health illnesses; the health

outcomes and costs linked with obesity are astounding. These costs vary from \$147 billion to \$210 billion annually and by 2030, it is predicted that the medical expenses could rise between \$48 billion and \$66 billion each year (University of Georgia, n.d.).

Social changes are necessary to decrease obesity. The social conditions for children's health is a factor (Whitaker, 2011). According to Whitaker (2011), through social change, pediatricians could become more involved in developing strategies to prevent instead of treating socially-determined health issues in children. This approach could be accomplished by pediatricians supporting social changes to encourage human well-being and incite discussion about the necessities to obtain human well-being (Whitaker, 2011). Childhood obesity is a public health issue and it affects the health of children early on and later in life. Due to the high childhood obesity rates in the South, the results from this study could contribute to positive social change. This can be accomplished by providing southern states with information for creating state-specific policies, developing prevention programs, and increasing community awareness.

Problem Statement

Childhood obesity is a main public health problem in the United States as well as in other developing countries, and this epidemic is affecting the lives of millions of children (Wang & Lim, 2012). The direct impact of obesity on children and adolescents are limited, and the consequences of obesity is linked to health care costs. These costs are on the rise due to more outpatient and emergency room visits from children with a high BMI (Carey, Singh, Brown, & Wilkinson, 2015). In the United States, there are extensive socioeconomic, race, and ethnic disparities linked to childhood obesity. Racial

and ethnic disparities in childhood obesity exist with higher rates of Hispanic (22%) followed by Black (20%) children whereas non-Hispanic White (14%) children (Arteaga et al., 2015; Martinson, McLanahan, & Brooks-Gunn, 2012). For adults, the prevalence of obesity is greater in the South region at 30% compared to other regions (Arteaga et al., 2015).

The prevalence of childhood obesity increased in the previous 30 years, and one in three children are obese or overweight (Centers for Disease Control and Prevention, [CDC], 2015a). For instance, obesity is widespread among 12.7 million children and adolescents aged 2-19 years (CDC, 2015a). The rate of childhood obesity decreased in European countries compared to North America with 20% of children in school are either overweight or obese, and 5% of these children are obese (Wang & Lim, 2012). Furthermore, in the United States at least seven of the 10 states in the South had higher prevalence of childhood obesity for ages 10-17 (Trust for America's Health, 2014). Florida is ranked 38th for highest obesity rates among 10-17 years at 13.4%, whereas Georgia is ranked 17th with 16.5% obesity rates (Trust for America's Health, 2014).

There are a limited number of studies investigating the effect of neighborhood conditions on childhood obesity (Singh, Kogan, & van Dyck, 2010). A few studies have proposed that racial/ethnic minority children whose parents have a low educational level and low income tend to be overweight or obese (Zilanawala et al., 2015). Wang and Lim (2012) reported that future research is essential to comprehend the relationships among obesity and socioeconomic status (SES). The occurrence of poverty is higher in rural areas and no studies appear to have been conducted on the effect of family income on

children's physical activities in a rural setting (Cottrell et al., 2015). Studying the contribution of family and child characteristics can help explain the risk of overweightness and obesity during early childhood have been emphasized in some studies (Zilanawala et al., 2015). Krueger, Jutte, Franzini, Elo, and Hayward (2015) reported that children's living arrangements had been connected to health outcomes such as asthma and obesity. Sedentary behaviors, such as watching television, might be harmful to children's physical health (Atkin et al., 2015), thus extended periods of this behavior should be reduced. It is still uncertain which types of sedentary behaviors are more detrimental than other ones (Atkin et al., 2015).

Purpose of the Study

The purpose of this quantitative correlational study was to test for significant state differences in childhood obesity prevalence in the South region. I explored geographical disparities in childhood obesity and overweightness after adjusting for individual family health and activities, sociodemographic, physical activity, and neighborhood safety and support among 10-17 year olds in Florida and Georgia. Thus, the project could add to the existing literature related to childhood obesity health disparities but focus on the South region where more research is needed (Meyers et al., 2015). By targeting Florida and its bordering state of Georgia, the data could provide additional insight on childhood obesity in these states.

Research Question(s) and Hypotheses

To assess the association of the independent variables on the dependent variable BMI, the following questions and hypotheses were developed. Logistic regression analysis was used to measure the predictors of BMI.

RQ1: Is there an association between neighborhood safety and support and BMI among 10-17 year olds in Florida and Georgia?

H₀1: There is no association between neighborhood safety and support and BMI among 10-17 year olds in Florida and Georgia.

H_a1: There is an association between neighborhood safety and support and BMI among 10-17 year olds in Florida and Georgia.

RQ2: Is there an association between physical activity and BMI among 10-17 year olds in Florida and Georgia?

H₀2: There is no association between physical activity and BMI among 10-17 year olds in Florida and Georgia.

H_a2: There is an association between physical activity and BMI among 10-17 year olds in Florida and Georgia.

RQ3: Is there an association between family health and activities and BMI among 10-17 year olds in Florida and Georgia?

H₀3: There is no association between family health and activities and BMI among 10-17 year olds in Florida and Georgia.

H_a3: There is an association between family health and activities and BMI among 10-17 year olds in Florida and Georgia.

RQ4: Is there an association between sociodemographics and BMI among 10-17 year olds in Florida and Georgia?

H₀4: There is no association between sociodemographics and BMI among 10-17 year olds in Florida and Georgia.

H_a4: There is an association between sociodemographics and BMI among 10-17 year olds in Florida and Georgia.

Theoretical Foundation of the Study

The theoretical framework used to guide this study is Bandura's (1986, 2004) social cognitive theory (SCT), originally known as social learning theory. SCT is well known in health education and can be useful for developing interventions to decrease childhood obesity (Glanz, Rimer, & Viswanath, 2015; Sharma, Wagner, & Wilkerson, 2006). It can be used to describe why individuals develop and continue health behaviors across a variety of population groups. The central principle of the SCT is that human behavior is a result of an interaction between behavioral, environmental, and personal factors (McCabe, Plotnikoff, Dewar, Collins, & Lubans, 2015). According to McCabe et al. (2015), the SCT has been broadly used in adolescent health behavior research and substantial evidence supports the theoretical constructs to justify physical activity behaviors among adolescents. Glanz, Rimer, and Viswanath (2015) suggested that studies should focus more on facilitative environmental change and incentive motivation to change behaviors associated with obesity.

The SCT was chosen to guide this study because it can be easily applied. It permits researchers and professionals to comprehend an extensive assortment of health

issues, by recognizing how learning occurs as well as the things that affect human behavior (Glanz et al., 2015; Sharma & Romas, 2012). The SCT allows structural factors to be combined with personal factors which are not seen in the other behavioral theories (Sharma & Romas, 2012). The SCT has been used in behavioral research for predicting physical activity behavior and predicting obesity behaviors (Sharma & Romas, 2012). Also, it can be used as a framework to develop intervention programs to reduce childhood obesity (Glanz et al., 2015).

There are several concepts of SCT, which include the following: (a) self-efficacy, (b) reciprocal determinism, (c) collective efficacy, (d) observational learning, (e) outcome expectations, (f) incentive motivation, (g) facilitation, (h) self-regulation, and (i) moral disengagement (Glanz et al., 2015). The authors implied these concepts can be classified into five categories such as psychological determinants of behavior, observational learning, self-regulation, moral disengagement, and environmental determinants of behavior (Glanz et al., 2015). For example, when it comes to children making sensible eating choices their abilities are reduced hence makes them more reliant on external factors. As indicated in the SCT, environmental factors impact human behavior and the participant behavior will not alter until the environment support the latest action (Glanz et al., 2015; Nyberg, Sundblom, Norman, & Elinder, 2011).

The physical environment encompasses children having access to healthy food as well as opportunities for physical activities (Nyberg et al., 2011). Also, nutrition programs are based on concepts from the SCT. Within the social environment, teachers, as well as parents play a vital role in motivating children to be physically active and

healthy eating (Berlin, Norris, Kolodinsky, & Nelson, 2013; Nyberg et al., 2011). By increasing people's confidence that they have the capability to execute behaviors that will result in desired outcomes is known as self-efficacy (Glanz et al., 2015). Self-efficacy is a key construct in SCT; for example, parental self-efficacy to aid their children with healthy eating habits and encouraging physical activity (Nyberg et al., 2011).

The SCT constructs can be used to answer the proposed research questions for this study. These constructs can be used to predict the behaviors of 10 to 17 year olds in Florida and Georgia. For example, the self-efficacy construct can be used to measure family and health activities such as the amount of time spent watching TV, number of days of physical activity, and how many days family eats meals together (Glanz et al., 2015). The SCT contains constructs such as observational learning, modeling, and self-efficacy (Glanz et al., 2015). Based on the SCT, the environment and the individual influence each other and this lead to social and individual change (Glanz et al., 2015). The SCT could help identify the social, environmental, and individual factors that may impact children and adolescents ability to be active and eat healthy.

Nature of the Study

A quantitative approach was selected to test the SCT as well as to measure the relationships between independent and dependent variables. This method allows data collection at a single point of time (Creswell, 2009). To analyze the numerous factors on childhood obesity, independent variables such as individual family health and activities, sociodemographic, physical activity, and neighborhood and community characteristics are examined. The family health and activities variable include (a) family eat meals

together; (b) time spent watching TV, videos, playing video games; (c) time spent with a computer, cell phone, or electronic device; and (d) time spent reading for pleasure (DRC, n.d.d.). Some of the sociodemographic variables include the (a) gender of child, (b) age of the child, (c) race and ethnicity, (d) family structure, (e) the income level of the household, and (f) parents' education level (DRC, n.d.d.). Also, the physical activity variable includes the number of days of physical activity during the week (DRC, n.d.d.). Neighborhood safety and support consists of children living in safe communities, living in supportive neighborhoods, and with the presence of neighborhood amenities. The dependent variable BMI will be used to measure childhood obesity and overweightness (DRC, n.d.d.). Data was obtained from the National Survey of Children's Health. The population-based survey data were collected from the parents of children and adolescents 10-17 years old living in the household. A cross-sectional design, logistic regression analysis, and correlational analysis was used to collect the numerical data. Also, data analysis was carried out through Statistical Package for the Social Sciences (SPSS).

Literature Search Strategy

The literature search strategy for this study consisted of library databases, search engines, and textbooks. Scholarly peer-reviewed journals with full-text research studies within the publication date of 2010-2016 were selected for this literature search. Several library databases and scholarly peer-reviewed journals with full text were chosen such as Academic Search Premier, CINAHL & MEDLINE Simultaneous Search, CINAHL Plus with Full Text, Education Research Complete, ERIC, MEDLINE with Full Text,

ProQuest Nursing & Allied Health Source, PsyINFO, and PubMed. The search engine Google Scholar were used to find research articles related to the childhood obesity. Also, I conducted Internet searches on public health sites such as CDC, Kaiser Family Foundation, and National Institutes of Health. The key search terms and combination of words included the following: *childhood obesity*, *physical activity*, *neighborhood safety*, *childhood obesity and SCT*, *childhood obesity and NSCH*, and *childhood obesity rates in Florida and Georgia*. Also, the terms *race/ethnicity and childhood obesity*, *screen time and childhood obesity*, *sedentary behavior and childhood obesity*, *racial disparities and childhood obesity*, and *parents and childhood obesity* were also searched. A comprehensive literature review is provided to offer additional information on risk factors linked to childhood obesity.

Literature Review Related to Key Variables and/or Concepts

Prior research studies have shown various factors such as income, race and ethnicity, family structure, physical activity, neighborhood safety and amenities, and screen time can impact childhood obesity (Bethell, Simpson, Stumbo, Carle, & Gombojav, 2010). These factors intermingle in different ways in each state and disproportionately affect racial and ethnic groups residing there (Bethell et al., 2010). A study by Martinson et al. (2012) showed that minority status was linked to a higher risk of becoming overweight. Native-born White children have a lower risk of being overweight than Black and Hispanic children of native-born mothers in the United States (Martinson et al., 2012). The authors work supported earlier literature that a significant adverse socioeconomic gradient in child overweightness and obesity for White children is

evident but not for non-White children (Martinson et al., 2012). Tandon et al. (2012) addressed the impact of family environment on childhood obesity. These family characteristics may be affected by family income or parents' educational level which can add to the differences in children's physical activity, sedentary behavior, and in the long run their weight status. Families with lower SES home environments offered lesser opportunities for physical activity but more sedentary behavior (Tandon et al., 2012). Wang and Lim (2012) and Zilanawala et al. (2015) provided information on the variable BMI. Children with a high BMI during early childhood develop chronic health conditions as well as diabetes and hypertension (Wang & Lim, 2012). Based on the literature parental involvement, race/ethnicity and income level has an impact on childhood obesity.

Tandon et al. (2012) and Wang and Lim (2012) offered evidence on the association between SES and obesity which differed by demographic and environmental factors. A lower SES was linked to poor health outcomes in children, which can lead to adult disparities. Also, children living in lower SES households have a tendency to be overweight or obese (Tandon et al., 2012; Wang & Lim, 2012). Cottrell et al. (2015) provided information on the high poverty rates in the Southeast regions. Children and adolescents from the south living in poor communities are more likely to be obese and less physically active compared to children in other locations (Cottrell et al., 2015). Thus, disadvantaged children are not inspired to play outside because of their parent's fear of safety concerns in the neighborhood (Ryabov, 2015). Melkevik et al. (2015) presented evidence on using electronic media devices such as personal computer, video

games, and television viewing as risk factors for children being overweight or having a higher BMI. Although, there is conflicting evidence in regard to the types of electronic media device used and across gender (Melkevik et al., 2015). This literature review includes variables associated with childhood obesity such as family health and activities, sociodemographic, physical activity, and neighborhood safety and support.

Family Health and Activities

According to Maher, Olds, Eisenmann, and Dollman (2012), there are a limited number of studies that have explored screen time and moderate-to-vigorous physical activity (MVPA). One study found that children aged 7 to 12 in the United States are 3-4 times prone to be obese due to not meeting screen time and physical activity guidelines (Maher et al., 2012). Another study indicated that children 14 to 18 years old in the United States had an increased risk of being overweight (Maher et al., 2012). The study showed low physical activity and high screen time was linked to children being overweight (Maher et al., 2012). Prior research search studies showed children living in Western countries had low levels of MVPA and spent more time participating in sedentary activities (Guinhouya, 2012). Maher et al. (2012) randomly selected 2,200 Australians aged between 9 and 16 years to take part in the Australian National Children's Nutrition and Physical Activity Survey. The purpose of the study was to establish which of the two behaviors MVPA or television viewing had a stronger association with overweightness and obesity. A computer-assisted face-to-face interview was used to collect demographic information, and statistical analysis consisted of logistic regression. This analysis was used to calculate the odds ratio of the weight category

combined with the screen time and MVPA categories done on girls and boys independently (Maher et al., 2012). One of the strengths of the study was the relationships between screen time, MVPA, and weight status, which were more consistent and higher among boys than girls. It is not clear why this is the case. Based on the results, weight status was strongly linked to screen time instead of physical activity which differs from the two investigations conducted in the United States (Maher et al., 2012). Physical activity was more significant for one study whereas both screen time and physical activity was of equal importance in the other study (Maher et al., 2012).

Since the bulk of past research studies focused more on television, it was identified as a gap (Carson, Pickett, & Janssen, 2011; Wethington, Pan, & Sherry, 2013). Wethington et al. (2013) stated that time spent watching television (TV), video games, or videos are possible risk factors for childhood obesity. Also, academic, developmental, clinical, and behavioral factors are also linked to an increased amount of TV viewing (Sisson, Broyles, Newton, Baker, & Chernausedk, 2011). TV viewing is connected to weight status because it reduces metabolic rate, supersedes physical activity, and increases dietary intake (Wethington et al., 2013). The American Academy of Pediatrics (AAP) advised parents not to have a TV in their child's bedroom. Young children older than 2 years of age should not have over 2 hours of screen time per day (Wethington et al., 2013). In the United States about 33% of children exceed AAP recommendations of less than 2 hours per day of video and TV viewing (Sisson et al., 2011). Regardless of these recommendations, 8 to 18-year olds spend about 7.5 hours every day with

electronics and media devices with about 4.5 hours of this time watching TV (Wethington et al., 2013). Prior cross-sectional studies showed a positive association with TV viewing time and TV in the bedroom (Wethington et al., 2013). Thus, based on the research increased screen time and lack of physical activity are risk factors that could lead to childhood obesity.

A cross-sectional study conducted by Wethington et al. (2013) contained data from the 2007 NSCH. The random-digit dial telephone survey occurred between 2007 and 2008 (Wethington et al., 2013). The survey was administered to a total of 1,800 households per state which included 91,642 children from birth to 17 years of age in the total sample (Wethington et al., 2013). After exclusions, a total of 23,416 children aged 6 to 11 years old and 29,005 adolescents aged 12 to 17 years old were included in the sample (Wethington et al., 2013). The purpose of the study was to detect the association of behavioral and sociodemographic characteristics with excess screen time among 6 to 11 and 12 to 17 year olds in Analysis I (Wethington et al., 2013). In Analysis II, the relationship of behavioral and sociodemographic characteristics linked to obesity among 12 to 17 year olds were explored in Analysis II (Wethington et al., 2013). In another study, Sisson et al. (2011) used data from the 2007 NSCH to investigate if a TV in the bedroom (BTV) impacts health and behavior. The design of the study was cross-sectional, and the randomly selected sample included 23,426 girls and 25,261 boys and. Children less than 6 years of age were excluded from the survey (Sisson et al., 2011).

Wethington et al. (2013) examined screen time as the dependent variable. The independent variables included sex, race/ethnicity, federal poverty level, physical

activity, adequate sleep, and the presence of BTV in Analysis I (Wethington et al., 2013). For Analysis II, the dependent variable was obesity status (Wethington et al., 2013). The independent variables were behavioral variables of sleep adequacy, BTV, physical activity, sociodemographic, screen time, characteristics of federal poverty level, sex, and race/ethnicity (Wethington et al., 2013). Whereas, Sisson et al. (2011) observed BTV as the independent variable and the variables of interest included social skills, community involvement, health status, family, and health habits. Also, the sociodemographic variables and covariates consisted of race/ethnicity, sex, age, family structure, family poverty level, and regions of the country. The analytical methods used in their study included simple logistic regression model for predicting the presence of BTV, weighted descriptive statistics to calculate the sample, and multicollinearity among social and behavioral outcomes (Sisson et al., 2011). The types of statistical analyses used in Wethington et al. (2013) study consisted of *t* tests for each independent variable, multivariate logistic regression to calculate adjusted and unadjusted odds ratios for obesity status and screen time >2 hours per day. Both of these studies explored television as either an independent or dependent variable and the impact television has on behavior.

Sisson et al. (2011) found that 49.3% of children have BTV and 49% watch more than 1 hour per day of TV. No prior studies have shown an association between an area of the country and family structure with BTV. Another study reported children in the South region were more likely to be overweight and have BTV (Sisson et al., 2011). The authors reported the non-West, not including Alaska, and non-two parent biological family structure correlated with greater odds of BTV (Sisson et al., 2011). It was

determined that BTV is significantly linked to higher odds of showing problematic social behaviors at 29% and overweight status in children 12 years and older at 44% (Sisson et al., 2011). A strength of the study was observing BTV independently as a risk factor and the addition of total viewing. Although, future research is necessary to explain these relationships because the mechanism of the relationships is unclear (Sisson et al., 2011). Wethington et al. (2013) results showed 20.8% of children aged 6 to 11 years, and 26.1% aged 12 to 17 years had more than 2 hours of screen time per day in Analysis I. For Analysis II, the authors found having a TV in the bedroom and exceeding screen time, were each linked with obesity ($OR=2.5$) among 12 to 17 year olds. Also, excessive screen time differed by race/ethnicity and sex. These results build upon prior studies highlighting the need for addressing children having a BTV in the bedroom and excessive screen time. In the future, it is vital to develop programs for individuals in the lower federal poverty level, tailored toward males, and non-Hispanic blacks since obesity and screen time affects this population at a higher rate (Wethington et al., 2013).

Ford et al. (2012) found obese children were not having family meals together. Race/ethnicity disparities were detected among young Black, Hispanic, and Asian/Pacific Island children. They had a higher number of unhealthy behaviors than White/non-Hispanic children. These unhealthy behaviors were more prevalent among Black and Hispanic adolescents (Ford et al., 2012). The authors study showed little physical activity, increased hours of weekday TV, small percentage eating breakfast, higher intake of sugary drinks, and low SES were present among Black and Hispanic children (Ford et al., 2012). The results of the study are consistent with other research studies (Ford et al.,

2012). Carson et al. (2011) conducted a study to observe television, video game, computer, and multiple risk behaviors among 10 to 16-year-old youth in Canada. The authors used a nationally representative cross-sectional survey based on the 2005/2006 Health Behavior in School-aged Children Survey with a total sample size of 9,764 students in Grades 6-10 (Carson et al., 2011). Data was gathered from a 1-year prospective cohort and the nonrepresentative subsample consisted of 3,300 students in Grades 9-10 during January 2006 and May 2006 (Carson et al., 2011).

Carson et al. (2011) examined multiple risk behaviors (MRB) as dependent variable and screen the independent variable. Demographics, physical activity, SES, parent trust and communication, and family structure were the covariates. Statistical analyses were completed using ordinal multiple logistic regression, repeated measure multiple logistic regression models, odds ratios and rate ratios. Based on the results, in both samples, there was a 50% increased risk of participation in MRB linked to high computer use (Carson et al., 2011). The variable high TV use identified in the cross-sectional sample was related to a modestly increased engagement in MRB. The study showed that various types of screen time behaviors have different effects on the health of adolescents (Carson et al., 2011). A weakness of the study was the use of self-reported data, and strength was using large sample size along with longitudinal analysis (Carson et al., 2011). Future research is needed to comprehend the influence of particular screen time behaviors on the health of adolescents to improve screen time recommendations (Carson et al., 2011). By examining these risk factors further can help reduce the burden of childhood obesity.

Sociodemographics

In the United States, not all racial groups are affected by the obesity epidemic in the United States (Frederick, Snellman, & Putman, 2014; Kirby, Liang, Chen, & Wang, 2012). There is a limited amount of evidence on the potential relationship between obesity and community racial/ethnic composition (Frederick et al., 2014; Kirby et al., 2012). Segregation is highly noticeable among racial and ethnic groups residing in the United States. Body weight and obesity rates vary across racial and ethnic groups. Current data from NHANES 2009-2010 showed about 17% of children and adolescents, and one-third of adults was obese (Frederick et al., 2014; Kirby et al., 2012). Around, 33% of White women are obese compared to 50% Black women (Frederick et al., 2014; Kirby et al., 2012). Racial and ethnic differences seen in factors such as education and income. It is a significant association between obesity and lower educational attainment and lower income (Frederick et al., 2014; Kirby et al., 2012; Sen & Patel-Dovlatabadi, 2012). Prior studies in obesity have shown racial disparities exist among SES groups for adolescents. Socioeconomic disparities in adolescent obesity have either increased, decreased, or remained the same over time based on evidence from past research studies (Frederick et al., 2014; Kirby et al., 2012; Sen & Patel-Dovlatabadi, 2012). Physical activity and food patterns were impacted by socioeconomic background (Frederick et al., 2014; Kirby et al., 2012; Sen & Patel-Dovlatabadi, 2012). Several studies showed a link between low SES and obesity among children and adolescents living in developed countries (Kachi, Otsuka, & Kawada, 2015). In Japan, there is a reduced number of

findings that explored the SES inequalities of the obesity risk factors among children and adolescents (Kachi et al., 2015).

Kachi et al. (2015) explored the association among overweight and SES on a sample of Japanese children aged 6-18 years old. For this particular study, data was taken from the 2010 National Health and Nutritional Survey (NHNS) and the 2010 Comprehensive Survey of Living Conditions (CSLC). The authors used a cross-sectional design which included a self-administered survey that was circulated to participants in advance and gathered later by trained staff during when they visited the home (Kachi et al., 2015). The sample size consisted of 397 children and 397 adolescents (Kachi et al., 2015). The overweight prevalence variable was a combination of overweight and obese groups. Another variable, socioeconomic status, included parental educational attainment, household income, household expenditure, and parental occupation class (Kachi et al., 2015). Age, gender, and maternal weight status were the confounding variables (Kachi et al., 2015). A study by Frederick et al. (2014) examined the socioeconomic disparities in obese adolescents aged 12-17 years old. The data acquired for the study is from the 1998-2010 NHANES and 2003-2011 NSCH (Frederick et al., 2014). The authors did not find any significant increases in obesity rates on the variables education and family income on children aged 2-5 years old or 6-11 years old (Frederick et al., 2014). Thus, these findings are consistent with past research using NHANES data (Frederick et al., 2014).

Kachi et al. (2015) used multilevel logistic regression analysis to observe associations between overweight and SES. They found 12.3% of children and 9.1% of

adolescents were overweight (Kachi et al., 2015). The frequency of overweight estimated at 26.3% higher for mothers of children with lower than a high school education compared to 11.0%-12.1% of mothers with a college degree (Kachi et al., 2015). According to Frederick et al. (2014), there were major differences in obesity rates among adolescents with the parental education variable based on the NHANES and NSCH surveys. The rates of obesity among adolescents whom parents have college degrees decreased but increased among less-educated families in the past few years (Frederick et al., 2014). Adolescents living in middle-income homes and having low expenditure levels are more likely to be overweight. Japanese children growing up in lower household incomes and expenses were at risk for being overweight (Kachi et al., 2015). In another study, the authors stated there was an inverse association to parental education and being overweight (Kachi et al., 2015). Further research is vital to examine more carefully how access to food facilitates detected correlations among overweight and household income. To prevent childhood obesity, it is necessary to include SES indicators (Kachi et al., 2015).

According to Frederick et al. (2014), the rise in health disparities is a result of growing differences in physical activity and calorie consumption. There was a decrease in energy intake among children from educated and wealthy homes. Also, children with a sedentary lifestyle do not burn up enough calories to make up for what they have ingested (Frederick et al., 2014). Research studies showed children of college-educated parents are more physically active than children of less-educated parents (Frederick et al., 2014). For instance, this may be due to low SES children living in neighborhoods that do

not facilitate a physically active lifestyle. Additional research is vital to gain a better understanding of the leading causes of health disparities (Frederick et al., 2014). Further research on the economic and health risks of childhood obesity is necessary for subgroups and whole populations (Frederick et al., 2014).

Dixon, Pena, and Taveras (2012) conducted a systematic review of published literature on various factors linked to childhood obesity. It is documented that racial/ethnic disparities exist in childhood obesity. Based on data from NHANES 2007-2008, approximately 15.3% of non-Hispanic white children, 20.0% of non-Hispanic black children, and 20.8% of Mexican American children ages 2-19 had a BMI \geq 95th percentile (Dixon et al., 2012). In another review of the literature, approximately, 9.1% of non-Hispanic black girls have severe obesity compared to 3.5% of non-Hispanic white girls and 5.1% of Hispanic girls ages 2-19 from 1976 to 2006 (Dixon et al., 2012).

A cross-sectional study by van Vliet, Gustafsson, Duchon, and Nelson (2015) examined how social inequality, age, gender, and parental SES were linked to overweight and obesity in Swedish girls and boys aged 7-17. The data for the study were obtained from a questionnaire completed by the parents with a total sample size of 263 boys and girls (van Vliet et al., 2015). For statistical analysis, the chi-square test was used to measure non-parametric variables, the *t*-test to measure continuous variables, and to gauge the perception of overweight a logistic regression modeling was used (van Vliet et al., 2015). The authors studied gender differences as well as the extent to which disparities in obesity among non-Hispanic Whites and African-Americans occur within specific income and educational groups (Sen & Patel-Dovlatabadi, 2012).

Sen and Patel-Dovlatabadi (2012) used data obtained from the southern region between the neighboring states of Louisiana, Alabama, and Mississippi. In the United States, obesity rates were the highest in the state of Mississippi (Sen & Patel-Dovlatabadi, 2012). The data were extracted from the Behavioral Risk Factor Surveillance System (BRFSS). The participants were interviewed via telephone using state-based health surveys which contained information on access to care, preventive health practices, and health risk behaviors (Sen & Patel-Dovlatabadi, 2012). The sample pool size included African Americans and non-Hispanic Whites from all three states with a total of 79,676 participants (Sen & Patel-Dovlatabadi, 2012). In their study, the dependent variable BMI was measured as a dichotomous variable (obese if $BMI \geq 30$ and not obese if $BMI < 30$) and income and education are the independent variables (Sen & Patel-Dovlatabadi, 2012). SES category were established by joining education and income together. Statistical analysis included univariate analyses, and the main statistical method was multivariate logistic regressions to project the racial gap in obesity risk for the whole sample and the given educational and income groups (Sen & Patel-Dovlatabadi, 2012). The relative-risk ratio (RR) and risk difference (RD) was used to measure the magnitude of the racial gaps. The authors used STATA version 11 for analyses (Sen & Patel-Dovlatabadi, 2012).

Based on the findings, in males < 13 years social inequality in overweight and obesity was observed, and the perception of overweight is usually among females ≥ 13 years (van Vliet et al., 2015). The rates of overweight and obesity were 14% for males and 15% for females using the ISO-BMI classification compared to 26% for males and

36% for females using the WC (van Vliet et al., 2015). No major gender variances in the rate of overweight and obesity found using the WC or ISO-BMI classification. A correlation was found in age and gender among males < 13 years with a low maternal SES and increased rate of overweight and obesity, and low parental education level for males \geq 13 years (van Vliet et al., 2015). In females \geq 13 years old, there was a relationship between high ISO-BMI and low paternal occupational status (van Vliet et al., 2015). Also, females \geq 13 years old were more prone to view themselves as overweight or fat regardless of their sizes compared to younger males and females (van Vliet et al., 2015). Further research is needed to determine age and gender differences among individuals view of overweight and the degree social inequality increases their risk for overweight and obesity (van Vliet et al., 2015).

According to Sen and Patel- Dovlatabadi (2012) obesity rates were the highest among African American males (30.1%) and African American females (47.4%) compared to non-Hispanic White males (29.0%) and (25.8%) non-Hispanic White females. The gap continues to be high in education, income, and obesity for females than males (Sen & Patel-Dovlatabadi, 2012). Additional research is needed to explore racial differences as it relates to obesity like physical activity and diet within educational and income groups (Sen & Patel-Dovlatabadi, 2012). Dixon et al. (2012) reported obese white children are not prone to be obese as adults compared to black children according to the results from the Bogalusa Hearty Study. The findings from SEARCH for Diabetes showed higher percentages of Type 2 diabetes amongst Hispanic, African American, American Indian, and Asian American adolescents (Dixon et al., 2012). The authors

concluded more research is needed to comprehend the factors related to racial/ethnic disparities in obesity prevalence (Dixon et al., 2012). Thus, current studies showed interventions during early childhood can help reduce childhood obesity (Dixon et al., 2012).

Physical Activity

When a child is physically active during childhood, this can help prevent childhood obesity. Play can be beneficial to children social and emotional growth as well as assist in the academic environment (Fan & Chen, 2012; Milteer, Ginsburg, Council on communications and media, Committee on Psychosocial aspects of child and family health, & Mulligan, 2012). Also, it helps build connections within the family and should be a part of school engagement. There is substantial empirical research on studies which have explored the relationships between children's health and neighborhood conditions (Fan & Chen, 2012; Milteer et al., 2012). For example, these studies have examined poverty and built environment in connection to the community (Fan & Chen, 2012; Milteer et al., 2012). The authors looked at risk behaviors and physical activities for health behavior outcomes too (Fan & Chen, 2012; Milteer et al., 2012). The National Center for Education Statistics showed that children living in urban areas with high poverty rates and large minority population are more likely to have lesser time at recess compared to children in urban areas. Thus, about 28% of children living in areas with high poverty rates had no break time for play activities (Miltier et al., 2012). The absence of physical activity among children could lead to sedentary lifestyles which can increase childhood obesity.

Milteer et al. (2012) reported boys may be impacted more by the reduction of recess time than girls. A few studies have indicated that males from low-income households are more physically active than males in wealthier households. However, other research studies showed boys from wealthier families are more physically active, and SES has no impact on the physical activity of girls (Guinhouya, 2012). Schools that promote recess permits children to partake in physical activity. It can be difficult for children to play safely in poor neighborhoods located in rural, urban, or suburban areas without the protection and supervision of an adult or parent (Guinhouya, 2012; Milteer et al., 2012). Therefore, this leads to children participating in more sedentary activities when they are not involved in physical activities (Guinhouya, 2012; Milteer et al., 2012). The neighborhoods may not offer equipped playgrounds. Thus, parents fear for the safety of their children due to violence which reduces their amount of physical activity outside the household (Guinhouya, 2012; Milteer et al., 2012). According to Datar, Nicosia, and Shier (2013) neighborhood safety is not researched as often and it can impact children's behaviors to be physically active. Milteer et al. (2012) suggested that community leaders and policy makers collaborate and make having a safe environment for children to play an urgent matter. The neighborhood environment can be used to help understand individual health behaviors as well clinical outcomes. It is well-known that the layout of cities and communities can encourage or prohibit physical activity in adults and children. Developing communities that are healthy is ongoing in the United States (Duke, Borowsky, & Pettingell, 2012; Rahman, Cushing, & Jackson, 2011). Therefore,

creating safe neighborhoods and receiving positive support from community members to improve the environment could decrease the rates of childhood obesity.

Neighborhood Safety and Support

Fan and Chen (2012) investigated the associations between children's health and neighborhood conditions on family functioning. The data used obtained from the 2007 NSCH with a final sample size of 53,023 children aged 6-17 years old (Fan & Chen, 2012). Children's health, neighborhood conditions (stressors/threats, physical resources, and collective efficacy), and family functions measures were studied. The structural equation modeling (SEM) was used to investigate the analytical model (Fan & Chen, 2012). This model established the types of covariates that impact family functioning and children's health (Fan & Chen, 2012). Based on the findings, environmental threats, and collective efficacy had a stronger association than physical resources for children's overall health. The covariates gender and age were linked to health and family functioning, particularly between females and youth (Fan & Chen, 2012). In regard to race, Black and Hispanic children have better family functioning than white children but the worse general health. Furthermore, the worse general health and family functioning was seen among single-mother and stepfamilies compared to children living in households with a higher income bracket (Fan & Chen, 2012). This study helps provides evidence that the associations among children's health and neighborhood conditions could be indirect and function through parental relationships and family activities (Fan & Chen, 2012). Kirby et al. (2012) proposed that the built environment and community features connected to racial/ethnic might have a critical influence on the weight status of

the residents. Future research is essential to explain the reason why Hispanic communities are linked with increased risk for obesity and higher BMI (Kirby et al., 2012).

Taylor et al. (2014) provided information on the association between obesity and the built environment. In one review article, there was a statistically significant positive link between children BMI and built environment. Another study showed noise, litter, and trash linked with obesity in children aged 3-12 years old (Taylor et al., 2014). For children, the relationships between obesity and physical environment varied by population density, age, and if the child or parent made the reports (Taylor et al., 2014). Thus, it is imperative the built environment features of neighborhood and socioeconomic levels are explored (Taylor et al., 2014). Prentice-Dunn and Prentice-Dunn (2012) summarized cross-sectional studies from 2000-2010 on the associations between sedentary behavior, physical activity (PA), and child weight status. The authors reviewed about 17 articles conducted in developed countries as well as in the United States. The sample population consisted of children aged 2-19 years old and used the following independent variables: PA, obesity, sedentary behavior and BMI as the dependent variable (Prentice-Dunn & Prentice-Dunn, 2012). Based on the mixed results, strong negative associations were found between childhood obesity and PA levels in five studies (Prentice-Dunn & Prentice-Dunn, 2012). Although, four of the five studies found sedentary behaviors to be significantly linked with obesity or overweight when using electronic or media devices (Prentice-Dunn & Prentice-Dunn, 2012). Most of the studies showed a positive correlation with child weight status and sedentary behaviors.

Sedentary behaviors and PA levels can be used to calculate child weight status (Prentice-Dunn & Prentice-Dunn, 2012). The authors suggested that further research is required to address impact of puberty on children's bodies because this can offer more details to describe the differences in PA (Prentice-Dunn & Prentice-Dunn, 2012).

Duke et al. (2012) used data from the 2007 NSCH to investigate the relationship between weight status, physical activities, and neighborhood context by using physical condition and several measures of perceived neighborhood social. The sample included 64,076 of parents or guardians of children ages of 6-17 years old (Duke et al., 2012). There are limited studies concerning neighborhood effects on childhood obesity, and the association is not clear. A few studies showed neighborhood amenities linked to a reduced risk of overweight or obesity, and others found no statistically significant association (Duke et al., 2012; Fan & Jin, 2013; Rahman et al., 2011). Rahman et al. (2011) reported lower-SES neighborhoods have a higher risk of obesity compared to wealthier neighborhoods because these communities have reduced access to food stores that provide healthy selections and recreational facilities. For instance, the level of physical activity has been clearly and positively associated with time spent outside the household. Because of this correlation, neighborhood safety becomes a key factor (Guinhouya, 2012). In this cross-sectional study, the dependent variables included aerobic physical activity and weight status to measure cardiovascular health (Duke et al., 2012). The independent variables for the four groups of neighborhood context include the following: physical condition, safety, resource availability, and social capital (Duke et al., 2012).

Duke et al. (2012) used additional independent variables to measure physical activity, and entered as control variables such as parent physical activity, TV in the bedroom, and parent report of youth health. Youth physical activity, TV in the bedroom, and family meals together were incorporated for determining weight loss (Duke et al., 2012). Data analysis included univariate statistics to describe health indicators and sample demographics. Pearson correlation was used to measure neighborhood context, and logistic regression analysis was used to measure the relationship between youth cardiovascular health and neighborhood factors (Duke et al., 2012). Based on the results, physical activity, and youth weight were significantly linked to the neighborhood characteristics (Duke et al., 2012). More research is needed to evaluate contributions from eating at school, neighborhood characteristics, family context, and physical education policy in aiding youth cardiovascular health (Duke et al., 2012). Also, more research is needed to determine an earlier and subsequently study plan to describe how variations in neighborhood resources, efficacy, and threats might worsen or improve the health of children in the neighborhood (Fan & Chen, 2012). The presence of safe intersections, crosswalks, sidewalks, and walkable communities can increase community activity levels based on rising evidence (Duke et al., 2012; Fan & Jin, 2013; Rahman et al., 2011). A combination of recreational, retail, residential, and commercial facilities can lead to additional physical activity among the residents, which can decrease obesity (Duke et al., 2012; Fan & Jin, 2013; Rahman et al., 2011).

Definitions

Body mass index (BMI): A measure to establish if a child is overweight or obese. BMI is calculated by dividing a person's weight and height (CDC, 2015bD).

Childhood Overweight: An individual with a BMI at or above the 85th percentile or below the 95th percentile for children and teens with same sex and age (CDC, 2015b).

Childhood Obesity: An individual with a BMI at or above the 95th percentile for children and teens with same sex and age (CDC, 2015b).

Family Health and Activities: Includes the variables family eats meals together, time spent watching TV, videos, or playing video games; time spent with a computer (DRC, n.d.). Also, cell phone, or electronic device; child has a TV, computer, or access to electronic devices in bedroom, and time spent reading for pleasure were incorporated in this category (DRC, n.d.).

Neighborhood Safety and Support: Includes children living in safe communities, living in supportive neighborhoods, and the presence of neighborhood amenities (DRC, n.d.).

Physical activity: Sixty or more minutes of physical activity; this includes moderate-intensity aerobic activity and vigorous-intensity activity per day among children and adolescents (CDC, 2015c).

Screen time: The AAP suggested that youth over two years of age have less than 2 hours per day with screens, and the child should not have a TV in their bedroom (Wethington, Pan, & Sherry, 2013).

Sociodemographic: Includes the sex of child, the age of child, race and ethnicity, family structure, the income level of household, parents' education level, and urban/rural location (DRC, n.d.).

Assumptions

For this study, no assumptions were made since the secondary data were obtained from the NSCH. It is assumed the parents or guardians answered the questions truthfully (Duke et al., 2012). These individuals self-identified as being more familiar with the child health status, health care needs, and behaviors for completing the questionnaire (Duke et al., 2012). The sample population is a nationally representative of the study population under investigation (Duke et al., 2012).

Scope and Delimitations

The data for this study were taken from the 2011/2012 National Survey of Children's Health (NSCH). Around 95,677 interviews were completed nationally and approximately 1,850 of these interviews was gathered per state (DRC, n.d.). The findings from NSCH are weighted to represent the population of noninstitutionalized children ages 0-17 residing in each state and on a national level (DRC, n.d.). The sample population was randomly selected for this study and was limited only to children 10-17 years old residing in Florida and Georgia. By choosing randomization, individuals have the same chance to be selected from the population, confirming the sample is a representative of the population (Creswell, 2009). Also, the NCHS data set contained the variables under study which are family health/activities, sociodemographic, physical activity, BMI, and neighborhood safety and support. In my study, the SCT was used.

Another concept linked to the study is theory of planned behavior (TPB). This theory used in health education for physical activity behavior and healthy eating habits (Sharma & Romas, 2012). The TPB not investigated because it does not explain behavior change or offer guidance for behavior modification (Sharma & Romas, 2012). According to Sharma and Romas (2012), the TPB does not include the following components that help shape individual's behaviors such as cultural factors, personality-related factors, and demographic variables. These components are vital for tackling childhood obesity.

Significance, Summary, and Conclusions

According to Singh, Kogan, and van Dyck (2010) in the United States racial inequalities detected more often than geographical disparities in childhood obesity. When compared to other developed countries, Greece had the highest rates of childhood obesity and ranked second is the United States. The goal set by Healthy People 2010 which was to have a childhood obesity of 5% by 2010 was obviously not met (Miyazaki & Stack, 2014). This research study could add to public health by providing evidence on geographical disparities in the South region. It can provide additional insight on which child health measures are contributing to the different rates of obesity in Florida and Georgia. According to the CDC (2012a), approximately 14.7% of adolescents in Florida were overweight with a BMI between (\geq 85th and $<$ 95th percentiles) and 10.3% were obese (\geq 95th percentile) in 2010.

About, 14.8% of adolescents were overweight in Georgia with a BMI between (\geq 85th and $<$ 95th percentiles) and 12.4% were obese (\geq 95th percentile) in 2010 (CDC, 2012a; CDC, 2012b). In regard to physical activity, merely 24.7% adolescents in Florida

were physically active for 60 minutes per day, and 19.4% had no physical activity (CDC, 2012a; CDC, 2012b). However, 23.7% of adolescents in Georgia were physically active for 60 minutes per day, and 17.6% were inactive (CDC, 2012a; CDC, 2012b). Also, 38.2% of adolescents in Florida compared to 39.2% in Georgia watched 3 or more hours per day of television on a school day in 2010 (CDC, 2012a; CDC, 2012b).

Meyers et al. (2015) reported that adult obesity rates were higher in the South; therefore, more data is necessary for this region and should be a central point for research as well as public policy. This study is unique because I will explore geographical disparities in childhood obesity and overweight once adjusting for family health/activities, sociodemographic, physical activity, and neighborhood and community characteristics in Florida and Georgia. Moreover, this study could provide supplementary data on childhood obesity in the South since more surveillance is needed to combat this issue. As a result, this research could support professional practice by expanding the knowledge base amongst public health practitioners, stakeholders, parents, and policymakers on state-specific childhood obesity rates in the South.

The results of this study could contribute to positive social change by helping these southern states develop state-specific policies and prevention programs which can reduce childhood obesity within the communities. Most importantly the findings could contribute to improving the health of children early on and decrease their risk of developing health conditions linked to childhood obesity later in adulthood. Also, this information can increase dialogue among community members within the southern states on childhood obesity to help eliminate health disparities among children and adolescents.

As previously mentioned, in the United States a public health issue is childhood obesity and it is affecting around 17% of children and adolescents (Riis, Grason, Strobino, Ahmed, & Minkovitz, 2012). The literature showed socioeconomic status, race and ethnicity, neighborhood, family structure, and behaviors could affect childhood obesity (Bethell, Simpson, Stumbo, Carle, & Gombojav, 2010; Martinson et al., 2012; Sisson et al., 2011). Childhood obesity rates vary in each state, and minorities are at an increased risk of becoming overweight (Bethell et al., 2010; Martinson et al., 2012; Sisson et al., 2011). According to Zilanawala et al. (2015), additional research is necessary to explain why some racial and ethnic groups have better health outcomes than others. Thus, by studying the causes of socioeconomic and racial/ethnic disparities in childhood obesity, this could be beneficial to public health professionals when designing programs among minority populations at highest risk (Hawkins et al., 2016).

Section 1, provided an introduction of the topic, childhood obesity, the purpose of the study, and the literature review. The research questions and hypotheses, theoretical foundation (SCT), and nature of the study of the study were presented. A comprehensive literature review of the key variables, definitions, assumptions, scope, and delimitations in the study were provided. The significance, summary, and conclusion of the study and implications for positive social change concluded this section. In Section 2, the research design and data collection was discussed.

Section 2: Research Design and Data Collection

Introduction

The purpose of this quantitative correlational study was to test for significant state differences in childhood obesity prevalence in the South region. I explored geographical disparities in childhood obesity and overweightness once adjusting for family health and activities, sociodemographic, physical activity, and neighborhood safety and support among 10-17 year olds in Florida and Georgia. Thus, the project could add to the existing literature related to childhood obesity health disparities but focus on the region where more research is needed according to Meyers et al. (2015). By targeting Florida and its bordering state of Georgia, the data could provide additional insight on childhood obesity in these states. Section 2 presents an outline of the methodology for this study based on the NSCH 2011/2012 data set. The research design and rationale, methodology, threats to validity, and summary were introduced for examining the study variables on childhood obesity. The IRB approval number for this study is 12-12-16-0416799.

Research Design and Rationale

The NSCH 2011/2012 is a national survey with a complex sample design, which includes a cross-sectional telephone survey with stratification by state. Also, the population type included households with landline or cell phone. Telephone interviews were conducted in English and Spanish to United States households with at least one or more children less than 18 years old (DRC, n.d.b.). Advance letters were sent to families explaining details of the study along with a toll-free telephone number to call if they had additional questions (DRC, n.d.b.). The design and process of the NSCH 2011/2012

survey is not released now for this study but will be released later. Although, the variables are comparable to the NSCH 2007 survey (Blumberg, Foster, & Frasier, 2012; CDC, National Center for Health Statistics, State and Local Area Integrated Telephone Survey, 2013; DRC, n.d.b.). The variables I used to guide this study were taken from the NSCH child health measures for children 10 to 17 years old. Data related to the independent variables consisted of the following: individual family health and activities, sociodemographic, physical activity, neighborhood safety and the dependent variable is BMI. A cross-sectional design was selected to answer the proposed research questions. Researchers can use this model to make comparisons at a precise point in time (Fink, 2010). It allows them to document information on the participants without affecting the study environment as well as compare several different variables at similar times (Fink, 2010; Institute for Work & Health, 2015).

The cross-sectional survey design can be used to describe the study's sample and offer baseline information at the beginning of the research study (Fink, 2010). The baseline data includes demographic data such as gender, age, education, income, and health (Fink, 2010). Also, it provides statistics on variables like current behaviors, attitudes, and knowledge. Furthermore, the relationships between other variables and demographic data could be investigated (Fink, 2010). Cross-sectional studies permit a bigger sample size (Prentice-Dunn & Prentice-Dunn, 2012; University of Michigan, 2010). There are not any major time and resource constraints with this design because it is less time consuming and more economical to perform than other research designs (Prentice-Dunn & Prentice-Dunn, 2012; University of Michigan, 2010). For instance, it

gives a quick picture to evaluate the prevalence of chronic or acute conditions in a population based on the data gathered (Prentice-Dunn & Prentice-Dunn, 2012; University of Michigan, 2010). Therefore, the results from this design provide characteristics of the population and disease which could be used to advance knowledge in public health (Prentice-Dunn & Prentice-Dunn, 2012; University of Michigan, 2010). The relationships found in cross-sectional studies are supported by longitudinal studies briefly then later by interventions for specific populations (Prentice-Dunn & Prentice-Dunn, 2012; University of Michigan, 2010).

Methodology

Population

About 40% of Hispanic and African American children are overweight or obese in the United States (letsmove.gov., n.d.). Childhood obesity is an issue and needs to be resolved if children born in 2000 or later will be diagnosed with diabetes early or later in life (letsmove.gov., n.d.). The NSCH were administered nationally in 2011-2012 with a total of 95,677 surveys completed (DRC, n.d.c.). The findings from NSCH are weighted to represent the population nationwide which consisted of noninstitutionalized children 0-17 years old in each of the 50 states and the District of Columbia (DRC, n.d.c.). The sample size nationally ranges between 91,000 and 102,000 and per state range 1,800-2,200 (DRC, n.d.c.). The population of interest for this study are children and adolescents ages 10 to 17 years residing in Florida and Georgia. Around 27.5% of children age 10 to 17 years are overweight or obese in Florida with an estimated

population of 470,715 (DRC, n.d.e.). About 35% of children age 10 to 17 years old are overweight or obese in Georgia with an estimated population of 363,667 (DRC, n.d.e.).

Sampling and Procedures Used to collect Data

The sampling frame utilized by the National Immunization Survey (NIS) were used for the NSCH. Since using the same sampling framework were more economical as well as efficient and permitted NSCH to use the NIS interview in designated households (CDC, National Center for Health Statistics, State and Local Area Integrated Telephone Survey, 2013). The selection process for the participants was random sampling to warrant that everyone in the population has an equal chance of being chosen.

Stratification of the population was determined by state and if the sample had cell phone or landline (Blumberg et al., 2012). The purpose of the survey design was to create samples representative of populations of children per state. To accomplish this task, state samples were intended to attain at least 1,700 completed interviews (Blumberg et al., 2012; Creswell, 2009).

The State and Local Area Integrated Telephone Survey (SLAITS) were used for sampling and data collection for NSCH. SLAITS was developed by the National Center for Health Statistics (NCHS) to gather information on a range of health topics at the local and state levels (DRC, n.d.b.). To screen the sample population, interviewers called households with landline telephone numbers using the list-assisted, random-digit-dial (RDD) method, with the addition of cell phone numbers using an independent RDD (Blumberg et al., 2012). The samples drawn once the estimated amount of telephone numbers for the NSCH interviews were reached. A percentage of the telephone numbers

in each area from the NIS sample was identified and included in the NSCH sample (Blumberg et al., 2012; CDC, National Center for Health Statistics, State and Local Area Integrated Telephone Survey, 2013). The sampling weights for the data were determined by one child per interview. Thus, any modifications to the sampling weight were applied before the cell phone and landline samples were combined. The sampling weight variable was NSCHWT (Blumberg et al., 2012; CDC, National Center for Health Statistics, State and Local Area Integrated Telephone Survey, 2013). By using survey weights, this ensures the final estimations are representative of every noninstitutionalized child in America from birth to 17 years in each state (Blumberg et al., 2012; CDC, National Center for Health Statistics, State and Local Area Integrated Telephone Survey, 2013).

Recruitment and participation. To determine eligibility for the study, a trained interviewer spoke to a member of the household which may be a guardian or parent (Blumberg et al., 2012; CDC, National Center for Health Statistics, State and Local Area Integrated Telephone Survey, 2013). This individual could answer questions regarding the health as well as the health care of the child in the sample (Blumberg et al., 2012; CDC, National Center for Health Statistics, State and Local Area Integrated Telephone Survey, 2013). Then the interviewer obtained verbal consent from the parent or guardian to participate in the study (Blumberg et al., 2012; CDC, National Center for Health Statistics, State and Local Area Integrated Telephone Survey, 2013). Any households without an adult aged 18 or over excluded from the screening section of the interview (Blumberg et al., 2012; CDC, National Center for Health Statistics, State and Local Area

Integrated Telephone Survey, 2013). The interviewers randomly called telephone numbers to detect families with children under 18 years old (Blumberg et al., 2012; CDC, National Center for Health Statistics, State and Local Area Integrated Telephone Survey, 2013). If more than one child lived in the household, one was randomly chosen for the comprehensive NSCH interview. Therefore, only one child chosen for the interview in the household (Blumberg et al., 2012; CDC, National Center for Health Statistics, State and Local Area Integrated Telephone Survey, 2013).

After the child is randomly selected, the parent or guardian answered Sections 1-5 of the survey which included questions asked for children ages 0-17 and Section 6 (early childhood) survey questions asked only for children ages 0-5 (DRC, 2013b). The rest of the questionnaire consisted of the following sections: Section 7 (middle childhood & adolescence); these questions are posed for children ages 6-17; whereas, Sections 8-11 of the survey are asked for children ages 0-17, and Section 12 (health insurance) questions asked for children who were uninsured when the survey was conducted (DRC, 2013b). Also, eligibility was determined by numerous telephone status questions asked to the cell phone sample in the first quarter of 2011 (CDC, National Center for Health Statistics, State and Local Area Integrated Telephone Survey, 2013). This sample was eligible if no landline telephone was present at home and if they were more likely to use cell phone regardless if they had a landline (CDC, National Center for Health Statistics, State and Local Area Integrated Telephone Survey, 2013). In the sample released in April 2011, anyone contacted by cell phone and had an eligible child at home were not screened like the previous sample in 2011 (CDC, National Center for Health Statistics,

State and Local Area Integrated Telephone Survey, 2013). The BMI of children of under the age of 10 were excluded from the study (CDC, National Center for Health Statistics, State and Local Area Integrated Telephone Survey, 2013).

Data collection. The data collected during February 28, 2011, to June 25, 2012 (Blumberg et al., 2012; CDC, National Center for Health Statistics, State and Local Area Integrated Telephone Survey, 2013). From the 95,677 completed detailed interviews, the cell phone sample, included 31,972 and 13,494 from the landline sample but only 3,424 were age appropriate (Blumberg et al., 2012; CDC, National Center for Health Statistics, State and Local Area Integrated Telephone Survey, 2013). Approximately, 24.2% of the interviewers were fathers, 68.6% were mothers, and 7.2% were guardians or kinfolks (Blumberg et al., 2012; CDC, National Center for Health Statistics, State and Local Area Integrated Telephone Survey, 2013). For landline samples, about 33 minutes was the standard interview length and 34 minutes for cell phone samples (Blumberg et al., 2012; CDC, National Center for Health Statistics, and State and Local Area Integrated Telephone Survey, 2013). If Section 6 or Section 7 of the survey were completed, then the interview was deemed to be finished. Before the interviews, the questionnaires were interpreted into several languages such as English, Mandarin, Spanish, Vietnamese, Cantonese, and Korean (Blumberg et al., 2012; CDC, National Center for Health Statistics, State and Local Area Integrated Telephone Survey, 2013).

In each state, information on child population overall as well as factors on household income, age, race/ethnicity, family structure, etc. were provided (CDC, National Center for Health Statistics, State and Local Area Integrated Telephone Survey,

2013; DRC, n.d.b.). Children assigned to one of five separate race/ethnicity categories which included the following: White, Black, Hispanic, Multi-racial, and Other. The NSCH interview completion rate included a cell phone sample of 41.2% and 54.1% for the landline sample (CDC, National Center for Health Statistics, State and Local Area Integrated Telephone Survey, 2013; DRC, n.d.b.). An Asian-language interviewer conducted 229 interviews and 4,905 were done by a Spanish-language interviewer (Blumberg et al., 2012; Center for Health Statistics, State and Local Area Integrated Telephone Survey, 2013). The NSCH interview concluded after the NIS interview in NIS-eligible households and it was shorter in length compared to NIS interview (CDC, National Center for Health Statistics, State and Local Area Integrated Telephone Survey, 2013). An incentive was given to encourage eligible families to participate in the study. This incentive helped increase response rates and the highest total value offered to them was \$15 (CDC, National Center for Health Statistics, State and Local Area Integrated Telephone Survey, 2013). Around, 18,728 households received an incentive for completing the interview (CDC, National Center for Health Statistics, State and Local Area Integrated Telephone Survey, 2013).

Access to data and permissions. The findings from the NSCH are available on the Data Resource Center website. This data is available to individuals, community health providers, parents, and researchers involved in maternal and child health (DRC, n.d.c.). Individuals could obtain a data set by completing a data form. Once the form is received, a Data User Agreement (DUA) must be completed and emailed back to the organization (DRC, n.d.c.). The requests are typically processed within five business

days once the DUA form returned (DRC, n.d.c.). Researchers can gain free access to the NSCH data sets to conduct their studies through the following: public-use documentation and data files, non-public-use data files, NCHS data linkage program, and national death index. Individuals can access vital health data through online resources and use tools to tailor and show data in a way that meets their personal needs (CDC, 2015d).

Power analysis. It is important to determine the sample size before conducting the study. The sample size can be small, medium, or large (Nayak, 2010). If a sample size is too small, it may not be sufficiently powered to recognize a difference among groups, or it may lead to Type II error (Nayak, 2010). A large sample size not suggested either. This kind of sample size can be a waste of time and money since the answer could have been found using a smaller sample (Nayak, 2010). Although, there is an increase in sample size when the power rise from 80% to 90% or 95% (Nayak, 2010). A power analysis was used to determine the sample size using software G*Power 3.1.9.2. The test family selected was *z* tests, statistical test was logistic regression, and the type of power analysis is a priori to compute required sample size. The power was 0.95 (set a high power to reject a null hypothesis that is not true), alpha level at 0.05 (the chance of Type 1 error occurring), and the effect size is 0.2 (Heinrich-Heine-Universität Düsseldorf, 2016; Mertler & Vannatta, 2013). For this study, the total sample size was 1,688 participants with normal distribution.

Instrumentation and Operationalization of Constructs

The NSCH was developed to evaluate how well the United States individual states and Washington D.C. meet the Maternal and Child Health Bureau's (MCHB) goals

and national performance measures (Blumberg et al., 2012). These findings from NSCH validate MCHB goals by offering an objective basis for state and federal program planning as well as evaluation. This survey conducted every 4 years (Blumberg et al., 2012). The funding for the NSCH 2011-2012 is arranged by U.S. Department of Health and Human Services and MCHB (CDC, National Center for Health Statistics, State and Local Area Integrated Telephone Survey, 2013; DRC, 2013a). The sampling and telephone interviews for NSCH directed by the National Center for Health Statistics. The National Center for Health Statistics and SLAITS conducted the survey. This survey is appropriate to the present study. The goal of NSCH is to estimate state and national level frequency for emotional, physical, and behavioral child health indicators of children aged 0 to 17 years old (CDC, National Center for Health Statistics, State and Local Area Integrated Telephone Survey, 2013; DRC, 2013a).

It also looks at the prevalence of family interactions and neighborhood characteristics as well as provide data on the health of the child population. This data can be used to identify health disparities by race/ethnicity, special health care needs, and socioeconomic status within and across states. Furthermore, the survey produces information about neighborhoods, children, and their families to help guide advocates, researchers, and policymakers (CDC, National Center for Health Statistics, State and Local Area Integrated Telephone Survey, 2013; DRC, 2011; DRC, 2013a). The NSCH offers a broad range of information related to children's health and well-being (Blumberg et al., 2012; DRC, n.d.b.). Also, it is the only survey that provides extensive information about children, families, and neighborhoods with sample sizes adequate for users to make

individual state analysis, comparisons between states, and at the national level (Blumberg et al., 2012; DRC, n.d.b.).

The NSCH provides information on topics such as emotional and physical health, as well as factors that might be associated with the well-being of children, such as family interactions, medical home, school experiences, parental health, and safe neighborhoods (DRC, n.d.c.). The NSCH questionnaire is composed of 11 sections which are initial demographics, child's health and functional status information, health insurance coverage, health care access and utilization, and medical home. The final sections are early childhood (0-5 years), middle childhood and adolescence (6-17 years), family functioning, parental health, neighborhood and community characteristics, and additional demographics (CDC, National Center for Health Statistics, State and Local Area Integrated Telephone Survey; DRC, n.d.d.). Since 2007, there were some significant additions to the study and omissions to the content of it (CDC, National Center for Health Statistics, State and Local Area Integrated Telephone Survey; DRC, n.d.d.).

The questionnaire was administered using the CATI system (Blumberg et al., 2012). This software displays the questionnaire on a computer screen which directs the interviewer through the questionnaire. The respondent answers were entered in the computer by the interviewer (Blumberg et al., 2012). The CATI program establishes if the selected response is within an acceptable range and saves it in a survey data file (Blumberg et al., 2012). Online assistance was available to the interviewer through text and help screens which decrease the time needed to transmit, process, and release data as well as supports data accuracy (Blumberg et al., 2012). Training was provided to the

interviewers, and they received information on the purpose and design of the study (Blumberg et al., 2012; DRC, n.d.c.). Once training was completed, interviewers had to obtain certification by passing the written and certification mock interview (Blumberg et al., 2012; DRC, n.d.c.). The NIS module and NSCH questionnaire was combined into one meeting (Blumberg et al., 2012; DRC, n.d.c.). The CATI system has the capability to verify answers if a response is within a reasonable range, follow skip patterns, and fill in state-specific information in questions as appropriate (Blumberg et al., 2012; DRC, n.d.c.). Pretesting was done on the questionnaire to ensure the CATI system was operating properly in 2006 (Blumberg et al., 2012; DRC, n.d.c.). The findings from the pretest were used to make revisions, then the questionnaire was finalized. The NSCH data is available to the public for free. Individuals can request a data set but must complete a Data User Agreement form to obtain it (Blumberg et al., 2012; DRC, n.d.c.).

Studies with the instrument. Slopen et al. (2016) used the NSCH data to estimate income and racial disparities in child adversity prevalence between Black, White, and Hispanic children born to United States born parents and immigrant parents. The sample included 84,837 children and nine measures from the 2011-2012 NSCH data were used to show the risks that affect children (Slopen et al., 2016). For statistical analysis purposes, data were stratified by family immigration history. Based on the results 49% of children were exposed to at least one adversity, whereas, 23% were exposed to two or more (Slopen et al., 2016). These adversities were found greater in children born to United States parents especially Black and Hispanic children compared to White children. The results are consistent with prior evidence on racial/ethnic

disadvantages (Slopen et al., 2016). The average number of adversities were higher among children born to United States parents than children born to immigrant parents while looking at income levels (Slopen et al., 2016). Racial/ethnic disparities in adversities were more prevalent among children from high-income families. The authors investigation highlights the need to view SES and race/ethnicity at the same time. This data emphasizes the importance of including immigration status when examining childhood adversity (Slopen et al., 2016).

Fisher-Owens et al. (2016) studied the state variation in children's oral health care access and oral health status using NSCH 2007 data. A multilevel approach was used to comprehend children's oral health. The dependent variables included oral health status and access to oral health care, whereas, child's state of residence was the independent variable (Fisher-Owens et al., 2016). Statistical analyses consisted of multilevel analysis, Peters-Belson method, and logistic regression. Based on the results, 17.5% of children in the United States lacked preventive dental care in the previous year (Fisher-Owens et al., 2016). The unadjusted rates of no preventive dental care varied at 9% in Hawaii to 26.8% in Florida (Fisher-Owens et al., 2016). There was a slight effect on the adjusted rates at 10.3% in Hawaii and 26.7% in Florida (Fisher-Owens et al., 2016). About 9% of children in the United States have fair/poor oral health with the highest reported in the West region (Fisher-Owens et al., 2016).

The authors found that geography is relevant because states differ considerably. The location of where a child lives has a significant impact on their access to oral health care and oral health status (Fisher-Owens et al., 2016). This data analysis could help

identify policies for states to improve oral health. Causality cannot be determined while using cross-sectional data (Fisher-Owens et al., 2016). Therefore, these findings should be observed as provisional and correlative (Fisher-Owens et al., 2016). Since the validity of surveys can be contingent upon non-sampling and sampling errors, the NSCH uses numerous ways to decrease these errors. The projected bias was 1.14 percentage points based on the seven key survey estimations (CDC, National Center for Health Statistics, State and Local Area Integrated Telephone Survey, 2013). Therefore, the bias fell within the 95% confidence interval which showed the nonresponse bias was lesser than the potential sampling error (CDC, National Center for Health Statistics, State and Local Area Integrated Telephone Survey, 2013).

Operationalization for each variable

The DRC website provided information on the question and the response options for the variables listed in the data set. The operational definition of the variable, how the variable is measured, and the calculation of the variable/scale score were provided for independent and dependent variables for this study (DRC, n.d.d.). Nominal and ordinal variables were stated as categorical variables. A dichotomous variable has only two categories or levels (Mertler & Vannatta, 2013).

Independent Variables

Neighborhood safety and support. Supportive neighborhoods, is composed of several subdomains which are social capital, perceived safety, neighborhood conditions, and neighborhood amenities (DRC, n.d.d.). The social capital questions derived from these four NSCH 2011/2012 survey questions. *Subdomain and variable code: Social*

capital (K10Q30) and Question: "People in this neighborhood help each other out" (DRC, n.d.d.). *Subdomain and variable code: Social capital (K10Q31) and Question: "We watch out for each other's children in this neighborhood"* (DRC, n.d.d.). *Subdomain and variable code: Social capital (K10Q32) and Question: "There are people I can count on in this neighborhood"* (DRC, n.d.d.). *Subdomain and variable code: Social capital (K10Q34) and Question: "If my child were outside playing and got hurt or scared, there are adults nearby who I trust to help my child"* (DRC, n.d.d.). The responses were coded: "1= definitely agree, 2 = somewhat agree, 3 = somewhat disagree, 4 = definitely disagree, and DK/REF = missing data" (DRC, n.d.d.). The level of measurement is ordinal/categorical.

The perceived safety question derived from the NSCH 2011/2012 survey question. *Subdomain and variable code: Perceived safety (K10Q40) and Question: "How often do you feel [SC] is safe in your community or neighborhood"* (DRC, n.d.d.). The responses were coded: "1 = never, 2 = sometimes, 3 = usually, 4 = always, and DK/REF = missing data" (DRC, n.d.d.). The level of measurement is ordinal/categorical.

The neighborhood conditions questions derived from three NSCH 2011/2012 survey questions. *Subdomain and variable code: Neighborhood condition (K10Q20) and Question: "In your neighborhood, is there litter or garbage on the street or sidewalk"* (DRC, n.d.d.). *Subdomain and variable code: Neighborhood condition (K10Q22) and Question: "How about poorly kept or rundown housing"* (DRC, n.d.d.). *Subdomain and variable code: Neighborhood condition (K10Q23) and Question: "How about vandalism such as broken windows or graffiti"* (DRC, n.d.d.). The responses were coded: "0 = no, 2

= yes, and DK/REF = missing data” (DRC, n.d.d.). The level of measurement is nominal/categorical.

The neighborhood amenities questions stemmed from three NSCH 2011/2012 survey questions. *Subdomain and variable code: Neighborhood amenities (K10Q11) and Question: “Sidewalks or walking paths” (DRC, n.d.d.). Subdomain and variable code: Neighborhood amenities (K10Q12) and Question: “A park or playground area” (DRC, n.d.d.). Subdomain and variable code: Neighborhood amenities (K10Q13) and Question: “A recreation center, community center, or boys or girls club” (DRC, n.d.d.).* The responses were coded: “0 = no, 1 = yes, and DK/REF = missing data” (DRC, n.d.d.). The level of measurement is nominal/categorical.

Physical activity. The exercise question originated from the NSCH 2011/2012 survey question. *Subdomain and variable code: Exercise (Ind1_5_11) and Question: “During the past week, on how many days did [SC] exercise, play a sport, or participate in physical activity for at least 20 minutes that made [him/her] sweat and breath hard” (DRC, n.d.d.).* The responses were code into four categories: “1 = 0 days, 2 = 1-3 days, 3 = 4-6 days, 4 = everyday, DK/REF = missing data” (DRC, n.d.d.). The level of measurement is ordinal/categorical.

Family health and activities. The family activities question stemmed from the NSCH 2011/2012 survey question. *Subdomain and variable code: Family activities (Ind6_8_11) and Question: “During the past week, on how many days did all the family members who live in the household eat a meal together” (DRC, n.d.d.).* The responses were coded into four categories: “0 = no days, 1 = 1-3 days, 2 = 4-6 days, 3 = everyday,

and DK/REF = missing data” (DRC, n.d.d.). The level of measurement is ordinal/categorical.

The media consumption questions stemmed from these four NSCH 2011/2012 survey questions. *Subdomain and variable code: Media consumption (Ind6_10_11) and Question:* “On an average weekday, about how much time does [SC] usually spend in front of a TV watching TV programs, videos, or playing video games” (DRC, n.d.d.). *Subdomain and variable code: Media consumption (Ind6_10b_11) and Question:* “On an average weekday, about how much time does [SC] usually spend with computers, cell phones, handheld video games, and other electronic devices, doing things other than schoolwork” (DRC, n.d.d.). The responses were coded into four categories: “0 = does not use electronic devices, 1 = uses electronic devices \leq 1 hour per day, 2 = uses electronic devices $>$ 1 but $<$ 4 hours per day, 3 = uses electronic devices \geq 4 hours per day, and DK/REF = missing data” (DRC, n.d.d.). The level of measurement is ordinal/categorical. *Subdomain and variable code: Media consumption (K7Q62) and Question:* “Does [he/she] have a TV, computer, or access to electronic devices in [his/her] bedroom” (DRC, n.d.d.). The responses were coded: “0 = 1, 1 = yes, and DK/REF = missing data” (DRC, n.d.d.). The level of measurement is nominal/categorical. *Subdomain and variable code: Activities (Ind5_6_11) and Question:* “Time spent reading for pleasure” (DRC, n.d.d.). The responses were coded: “0 = none, 1 = 30 minutes or less, 2 = 31 minutes to 1 hour, 3 = more than 1 hour, and DK/REF = missing data” (DRC, n.d.d.).

Sociodemographics. Race and ethnicity, income, education level, the sex of child, age, location, and family structure were used to measure socio-economic status.

Variable name and code: Sex of selected child (sex_11) and Question: “Is [SC] male or female” (DRC, n.d.d.). The responses were coded: “1 = male, 2 = female, DK/REF = missing data” and level of measurement is nominal/categorical (DRC, n.d.d.). Race was divided into five categories in past surveys but some of the categories were combined in 2011/2012. *Subdomain and variable code: Race and ethnicity of child (race4_11) and Question: “Is [Sc] White, Black, Hispanic, or Other”* (DRC, n.d.d.). The responses were coded: “1 = Hispanic, 2 = White, non-Hispanic, 3 = Black, non-Hisp, 4 = Multi-racial/Other, non-Hisp, and DK/REF = missing data” (DRC, n.d.d.). The level of measurement is nominal. Next, child age was categorized into two age groups and coded: “1 = 10 – 13 years and 2 = 14 – 17 years” (DRC, n.d.d.). The level of measurement is ordinal/categorical. The family structure variable (*famstruct_11*) includes parents living in the household. The responses were coded: “1 = two parent-biological or adopted, 2 = two parent- stepfamily, 3 = single mother, no father present, 4 = other family type, and DK/REF = missing data” (DRC, n.d.d.). The level of measurement is nominal/categorical. The income level of the child’s home (*povlev4_11*) was grouped into four groups. The responses were coded: “1 = 0-99% FPL, 2 = 100-199% FPL, 3 = 200-399% FPL, and 4 = 400% FPL or more” with the lowest level indicating poorest household (DRC, n.d.d.). The level of measurement is ordinal/categorical. The education of parents variable (*EDUC_MOMR*) or (*EDUC_DADR*) and *Question: “What is the highest grade or year of school (you have/*

[CHILD'S NAME]'s [MOTHER/FATHER TYPE] has) completed” (DRC, n.d.f.). The responses were coded: “1 = less than High School, 2 = High School Graduate, 3 = More than High School, and DK/REF = missing data” (DRC, n.d.f.). The level of measurement is ordinal/categorical. The variable (*STATE*) was recoded to (*State_Recode*) and the responses were coded as 0 = Florida and 1 = Georgia. The level of measurement is nominal/categorical.

Dependent Variable: BMI

Body mass index (BMI). BMI is a measure used to determine if a child is overweight or obese. The parent-reported weight and height estimates are used to measure BMI. It is computed by dividing a person’s weight and height and expressed as a percentile for children and teens after calculated. The BMI was not stated for any children below 10 years of age. In this study, the dichotomous variable BMI was combined into two categories. The (*BMICLASS*) variable is listed in the NSCH 2011/2012 data set (CDC, 2015b; DRC, n.d.d.). It was recoded as (*BMI_2groups*) and the responses coded as 0 = underweight and healthy weight and 1 = overweight and obese for this study (CDC, 2015b; DRC, n.d.d.). The cut-offs for BMI were decoded as follows: “underweight (< 5th percentile), healthy weight (\geq 5th percentile to < 85th percentile), overweight (\geq 85th percentile to < 95th percentile), and obese (\geq 95th percentile)” for children and teens of the same sex and age (CDC, 2015b; DRC, n.d.d.). The level of measurement for BMI is nominal/categorical.

Data Analysis Plan

According to Blumberg et al., (2012), to store the NSCH data collected for each sampled child, a SAS (version 9.1) data file was created. One record for each child was randomly chosen to be the subject of the interview. The CATI system was constructed to help prevent interviewer error when data were entered into the computer by completing consistency and range checks (Blumberg et al., 2012). Data cleaning was needed to explore missing values and remove invalid values. Any records that had missing responses for unspecified reasons were left missing. When conducting analyses, missing data is not suitable and regularly overlooked (Blumberg et al., 2012). There are special missing value codes included in the data file for anyone who would like to differentiate between the various types of missing values. The missing value codes are the following: (.A) added question, (.L) legitimate skip, (.M) missing in error, (.N) not in universe, and (.P) partially completed interview (CDC, National Center for Health Statistics, State and Local Area Integrated Telephone Survey, 2013). A numeric code was used to identify responses that the respondent did not know the answer or refused to provide the answer. These unknown answers are coded as “6, 96, or 996” and declined answers were coded as “7, 97, or 997” (CDC, National Center for Health Statistics, State and Local Area Integrated Telephone Survey, 2013).

It is vital that analysts check the data documentation and frequency lists to ensure the correct code were used for certain variables. If not, this can lead to incorrect calculations for variables measured using interval, ordinal, or ratio scales (Blumberg et al., 2012; CDC, National Center for Health Statistics, State and Local Area Integrated

Telephone Survey, 2013). Imputation was used to handle non-response, since, missing values for demographics, health, and neighborhood and community characteristics variables. To protect confidentiality of the participants, the child's exact age in months, the relationship of respondent to the child, household income, geographic information, and date of the interview is concealed in the data file (Blumberg et al., 2012; CDC, National Center for Health Statistics, State and Local Area Integrated Telephone Survey, 2013). It is not advisable for analysts to subset the NSCH data because it may delete vital information necessary for variance estimation. Although, the data can be subsetted to a precise state without compromising the design structure (Blumberg et al., 2012; CDC, National Center for Health Statistics, State and Local Area Integrated Telephone Survey, 2013). The cell phone sample is a new addition to the NSCH 2011/12. Therefore, the variable SAMPLE which includes landline and cell phone should be incorporated in the sample design (Blumberg et al., 2012; CDC, National Center for Health Statistics, State and Local Area Integrated Telephone Survey, 2013).

Research Question(s) and Hypotheses

To examine the association of the independent variables on the dependent variable BMI, the following questions and hypotheses were developed. Logistic regression analysis was used to measure the predictors of BMI.

RQ1: Is there an association between neighborhood safety and support and BMI among 10-17 year olds in Florida and Georgia?

H₀1: There is no association between neighborhood safety and support and BMI among 10-17 year olds in Florida and Georgia.

H_{a1} : There is an association between neighborhood safety and support and BMI among 10-17 year olds in Florida and Georgia.

RQ2: Is there an association between physical activity and BMI among 10-17 year olds in Florida and Georgia?

H_02 : There is no association between physical activity and BMI among 10-17 year olds in Florida and Georgia.

H_{a2} : There is an association between physical activity and BMI among 10-17 year olds in Florida and Georgia.

RQ3: Is there an association between family health and activities and BMI among 10-17 year olds in Florida and Georgia?

H_03 : There is no association between family health and activities and BMI among 10-17 year olds in Florida and Georgia.

H_{a3} : There is an association between family health and activities and BMI among 10-17 year olds in Florida and Georgia.

RQ4: Is there an association between sociodemographics and BMI among 10-17 year olds in Florida and Georgia?

H_04 : There is no association between sociodemographics and BMI among 10-17 year olds in Florida and Georgia.

H_{a4} : There is an association between sociodemographics and BMI among 10-17 year olds in Florida and Georgia.

Statistical tests. Descriptive statistics were used to describe the data gathered on the variables. The logistic regression model was used to detect group membership among

independent variables as determined by a dichotomous dependent variable. A control variable is a type of independent variable that can be used to measure its impact on the dependent variable (Creswell, 2009; Mertler & Vannatta, 2013). The sociodemographic variables were used as control variables. The results were interpreted with confidence intervals (95% CI) and an alpha level of (0.05) applied to all the analyses in the study. The odds ratio was calculated for the independent variables using the logistic regression coefficients (Creswell, 2009; Mertler & Vannatta, 2013). Data analysis were completed with the IBM SPSS 21 Statistics software.

Threats to Validity

External and internal threats are two types of threats to validity (Creswell, 2009; Trochim, 2006). When researchers conduct experiments, it is vital, they detect and decrease these risks. Generalizing is associated to external validity. Interaction of selection and treatment, interaction of setting and treatment, and treatment of history and treatment are three types of threats to external validity (Creswell, 2009; Trochim, 2006). To address the threat, interaction of selection and treatment, researchers can limit statements about groups to which the findings cannot be generalized (Creswell, 2009). To improve the threat, interaction of setting and treatment, the researchers should conduct more experiments in a different setting to determine if similar results will arise as in the original location (Creswell, 2009). The interaction of history and treatment threat can be improved by researcher if similar study is duplicated later to see if the same findings appear from the previous time. Also, threats of external validity can be improved in my

study by random selection of the population and have low dropout rates (Creswell, 2009; Trochim, 2006).

Internal validity is only applicable to research studies that show a causal relationship (Creswell, 2009; Trochim, 2006). This type of validity provides the researcher with evidence of what was done in the study was caused by the outcome. There are several types of threats to internal validity which include the following: history, maturation, testing, statistical regression, instrumentation, experimental mortality, and selection-maturation interaction (Creswell, 2009; Trochim, 2006). The validity of the NSCH depends on sampling and non-sampling errors (Fisher-Owens et al., 2016). Several methods were used to estimate bias. The findings showed that the sample population was more likely to reside in rural areas and areas with lower household density than with the nonresponding population. The analysis revealed that response biases had small impact on key survey estimates and the nonresponse adjustment to the weights significantly decreased the extent of those biases (Centers for Disease Control and Prevention, National Center for Health Statistics, State and Local Area Integrated Telephone Survey, 2013).

The same NSCH survey implemented in prior years was used to control for instrumentation validity in 2011/2012 survey but with some revisions. To control for instrumentation validity, the same NSCH survey used in prior years was used again in NSCH 2011/2012 but with some revisions. The survey undergoes extensive literature as well as technical expert panel review. To determine if the survey instrument was effective, cognitive interviews was performed with the 2007 NSCH CATI (Association of

Maternal & Child Health Programs [AMCHP], 2014; Centers for Disease Control and Prevention, National Center for Health Statistics, State and Local Area Integrated Telephone Survey, 2013). Once interviews completed the questionnaire was modified based on the proposed changes. Therefore, face validity is performed when evaluating findings with past years NSCH survey with findings from previous implementations of items (AMCHP, 2014). Threats to construct validity include insufficient measures of variables and definitions provided in the study. To ensure there are not any threats to construct validity the definitions and measures will come from professional literature or websites. Threats of statistical conclusion validity occur when researchers draw incorrect assumptions from the data due to insufficient statistical power (Creswell, 2009).

Ethical Procedures

Once verbal consent was obtained from the parent or guardian, this was recorded in the CATI system. The interviewer read a script to the participants about the survey, informed them their responses would be kept confidential, and they could withdraw at any time. Thus, participation in the NSCH is voluntary, and data is confidential. The NSCH follows strict procedures with agents and data collection contractors to avoid the release of confidential data in survey operations and data distribution. To protect the confidentiality of the children and respondents in the survey, responses for the race variable were broken down into three groups: African American or Black only, White only, and other race. The information given by the participants were used for statistical purposes and analysis based on the following laws: Confidential Information Protection and Statistical Efficiency Act (44 USC 3501) and the Public Health Service Act (42 USC

242m Section 308d). Any direct identifiers in the data set were removed; any effort to establish the identity of reported cases are forbidden by these laws. Therefore, anyone that uses this data set must obey these laws (Blumberg et al., 2012; CDC, National Center for Health Statistics, State and Local Area Integrated Telephone Survey, 2013). The archival data will remain confidential and stored in a secure location. Data will be destroyed after five years. There is no conflict of interest with secondary data within the work environment.

Summary

This section presented the research design and data collection for the study. A quantitative approach was used to conduct the study. Descriptive statistics were used to summarize the data gathered from the NSCH 2011/2012 data set. To depict the data and describe the association between dependent and independent variables the logistic regression model was used. The IBM SPSS 21 Statistics software was used for statistical analysis and G*Power analysis were used to calculate sample size. Section 3 included a presentation of the results and findings.

Section 3: Presentation of the Results and Findings Section

Introduction

This study was designed to test for significant state differences in childhood obesity prevalence in the South region of the United States. The child health measures individual family health activities, sociodemographics, physical activity, and neighborhood safety and support among 10-17 years in Florida and Georgia were explored. To examine the association of the independent variables on the dependent variable BMI, the following questions and hypotheses were developed. Logistic regression analysis was used to measure the predictors of BMI.

Research Question(s) and Hypotheses

RQ1: Is there an association between neighborhood safety and support and BMI among 10-17 year olds in Florida and Georgia?

H₀1: There is no association between neighborhood safety and support and BMI among 10-17 year olds in Florida and Georgia.

H_a1: There is an association between neighborhood safety and support and BMI among 10-17 year olds in Florida and Georgia.

RQ2: Is there an association between physical activity and BMI among 10-17 year olds in Florida and Georgia?

H₀2: There is no association between physical activity and BMI among 10-17 year olds in Florida and Georgia.

H_a2: There is an association between physical activity and BMI among 10-17 year olds in Florida and Georgia.

RQ3: Is there an association between family health and activities and BMI among 10-17 year olds in Florida and Georgia?

H_03 : There is no association between family health and activities and BMI among 10-17 year olds in Florida and Georgia.

H_a3 : There is an association between family health and activities and BMI among 10-17 year olds in Florida and Georgia.

RQ4: Is there an association between sociodemographics and BMI among 10-17 year olds in Florida and Georgia?

H_04 : There is no association between sociodemographics and BMI among 10-17 year olds in Florida and Georgia.

H_a4 : There is an association between sociodemographics and BMI among 10-17 year olds in Florida and Georgia.

Section 3 presents an outline of the data collection of secondary data set. It includes descriptive statistics of the sample and a report of the statistical analysis findings of the hypotheses. Also, the regression analysis and results are presented in tables and a summary of the findings are provided.

Data Collection of Secondary Data Set

Data collection for this study occurred during February 28, 2011 to June 25, 2012 (Blumberg et al., 2012; CDC, National Center for Health Statistics, State and Local Area Integrated Telephone Survey, 2013). As part of the recruitment process, interviewers randomly called telephone numbers to select households with children ages 0-17 (Blumberg et al., 2012; CDC, National Center for Health Statistics, State and Local Area

Integrated Telephone Survey, 2013). The interviewer randomly picked one child as the focus on the interview while the parent or guardian answered the questions.

Approximately, 95,677 participants completed the interviews and about 1,850 interviews were gathered per state (Blumberg et al., 2012; CDC, National Center for Health Statistics, State and Local Area Integrated Telephone Survey, 2013). The interview completion rate for the cell phone sample, included 31,972 and 13,494 from the landline sample but only 3,424 were age appropriate (Blumberg et al., 2012; CDC, National Center for Health Statistics, State and Local Area Integrated Telephone Survey, 2013).

For this study, the sample population of interest involved children ages 10-17 residing in Florida and Georgia. This sample is representative of the population and the findings from NSCH are weighted to represent the population nationwide (Blumberg et al., 2012; CDC, National Center for Health Statistics, State and Local Area Integrated Telephone Survey, 2013). The participants were selected by random sampling to ensure that everyone in the population has an equal chance of being selected. By using survey weights, this warrants the final values are representative of every noninstitutionalized child in America from birth to 17 years in each state (Blumberg et al., 2012; CDC, National Center for Health Statistics, State and Local Area Integrated Telephone Survey, 2013). The interview completion rate was 688 (40.8%) for cell phone sample and 1000 (59.2%) for the landline sample (Blumberg et al., 2012; CDC, National Center for Health Statistics, State and Local Area Integrated Telephone Survey, 2013). There were not any major discrepancies in the secondary data set from the plan presented in Section 2. Upon reviewing the actual data set there were some variables that were coded differently.

Results

A quantitative correlational research study using secondary data was conducted to test for significant state differences in childhood obesity prevalence in 10-17 year olds in Florida and Georgia. This study examined four research questions and associated hypotheses. The 2011/12 NSCH [SPSS] Indicator Data Set prepared by the Data Resource Center for Child and Adolescent Health, Child and Adolescent Health Measurement Initiative was used to analyze the data. Descriptive statistics and characteristics are provided to describe the sample population.

Descriptive statistics

This sample included data for 1,688 underweight to obese children ages 10 to 17 years old residing in Florida and Georgia. A total of 866 males (51.4%) and 820 females (48.6%) were included in the research study. Approximately, 1,060 (62.8%) of the population lived in Florida and 628 (37.2%) in Georgia. Regarding race/ethnicity, 316 (19.1%) reported Hispanic, 782 (47.4%) White, non-Hispanic, 426 (25.8%) Black, non-Hispanic, and 127 (7.7%) Multiracial/Other, non-Hispanic. About 1,118 (69.7%) of the population were underweight/healthy and 487 (30.3%) were classified as overweight/obese. Descriptive and demographic variables of the sample population are presented in Table 1. Roughly, 789 (48.3%) of the participants somewhat agree that people in the neighborhood help each other out. Around 874 (53.1%) of the participants “definitely agree” they watch out for each other’s children in their neighborhood (see Table 2).

Table 1

Descriptive Statistics of Sample Population

Sociodemographic characteristics	Frequency	Valid Percent
State		
Florida	1060	62.8
Georgia	628	37.2
Total	1688	
Residence		
Metropolitan area	1497	89.6
Non-metropolitan area	175	10.4
Missing	16	
Total	1688	
Age of child		
10-13 years	786	46.6
14-17 years	902	53.4
Total	1688	
Sex of child		
Male	866	51.4
Female	820	48.6
Refused	2	
Total	1688	
Race/ethnicity		
Hispanic	316	19.1
White, non-Hispanic	782	47.4
Black, non-Hispanic	426	25.8
Multi-racial/Other, non-Hispanic	127	7.7
Missing	37	
Total	1688	
BMI		
Underweight/Healthy	1118	69.7
Overweight/Obese	487	30.3
Missing	83	
Total	1688	

Note. Frequencies based on sampling weights.

Table 2

Descriptive Statistics for Neighborhood Safety and Support - Social Capital

Variable	Frequency	Valid percent
People in this neighborhood help each other out.		
1- Definitely agree	623	38.1
2- Somewhat agree	789	48.3
3- Somewhat disagree	132	8.1
4- Definitely disagree	91	5.5
Missing	53	
Total	1688	
We watch out for each other's children in this neighborhood.		
1- Definitely agree	874	53.1
2- Somewhat agree	552	33.6
3- Somewhat disagree	117	7.1
4- Definitely disagree	101	6.1
Missing	44	
Total	1688	
There are people I can count on in this neighborhood.		
1- Definitely agree	954	57.8
2- Somewhat agree	483	29.2
3- Somewhat disagree	117	7.1
4- Definitely disagree	97	5.9
Missing	38	
Total	1688	
If my child were outside playing and got hurt or scared, there are adults nearby who I trust to help my child.		
1- Definitely agree	1096	66.9

(table continues)

Variable	Frequency	Valid percent
2- Somewhat agree	383	23.4
3- Somewhat disagree	82	5
4- Definitely disagree	78	4.8
Missing	49	
Total	1688	

Regarding perceived safety in the neighborhood, 1,003 (60.3%) of the participants always feel safe in their community or neighborhood (see Table 3).

Table 3

Descriptive Statistics for Neighborhood Safety and Support - Perceived Safety

Variable	Frequency	Valid percent
How often do you feel [S.C.] is safe in your community or neighborhood?		
1- Never	29	1.7
2- Sometimes	166	10
3- Usually	466	28
4- Always	1003	60.3
Missing	25	
Total	1688	

About 1,472 (88.4%) of the participants reported no litter or garbage on the street or sidewalk in their neighborhood (see Table 4). Most of the participants 1,159 (69.8%) reported sidewalks or walking paths exist in their neighborhood (see Table 5).

Table 4

Descriptive statistics for Neighborhood Safety and Support domain for Neighborhood Conditions

Variable	Frequency	Valid percent
In your neighborhood, is there litter or garbage on the street or sidewalk?		
0- No	1472	88.4
1- Yes	193	11.6
Missing	24	
Total	1688	
How about poorly kept or [dilapidated/rundown] housing?		
0- No	1385	83.6
1- Yes	271	16.4
Missing	32	
Total	1688	
How about vandalism such as broken windows or graffiti?		
0- No	1534	92.3
1- Yes	128	7.7
Missing	26	
Total	1688	

Table 5

Descriptive Statistics for Neighborhood Safety and Support - Neighborhood Amenities

Variable	Frequency	Valid percent
Do sidewalks or walking paths exist in your neighborhood?		
0- No	501	30.2
1- Yes	1159	69.8
Missing	28	
Total	1688	
Does a park or playground area exist in your neighborhood?		
0- No	426	25.6
1- Yes	1240	74.4
Missing	23	
Total	1688	
Does a recreation center, community center, or boys' or girls' club exist in your community?		
0- No	541	33.1
1-Yes	1094	66.9
Missing	53	
Total	1688	

Nearly, 612 (36.7%) of the participants partook in physical activity for 4-6 days and at least 20 minutes in the past week (see Table 6).

Table 6

Descriptive Statistics for Physical Activity

Variable	Frequency	Valid percent
During the past week, on how many days did [child name] exercise, play a sport, or participate in physical activity for at least 20 minutes that made [him/her] sweat and breathe hard?		
0-days	200	12
1-3 days	412	24.7
4-6 days	612	36.7
Everyday	444	26.6
Missing	19	
Total	1688	

About, 620 (36.9%) family members who live in the same household reported eating a meal together for 4-6 days during the past week (see Table 7). Approximately, 723 (43.0%) of the participants watched TV more than 1 hour but less than 4 hours per day (see Table 8).

Table 7

Descriptive Statistics for Family Health and Activities – Family eats meals together

Variable	Frequency	Valid percent
During the past week, on how many days did all the family members who live in the household eat a meal together?		
0-days	77	4.6
1-3 days	384	22.8
4-6 days	620	36.9
Everyday	602	35.8
Missing	6	
Total	1688	

Table 8

Descriptive Statistics for Family Health and Activities – Time spent watching TV

Variable	Frequency	Valid percent
Time spent watching TV or videos on average weekday - - children age 1 to 17 years		
0-Does not watch TV	93	5.6
1-Watches TV 1 hour or less per day	577	34.3
2-Watches TV more than 1 hour but less than 4 hours per day	723	43.0
3-Watches TV 4 hours or more per day	288	17.1
Missing	6	
Total	1688	

Almost, 707 (42.7%) of the participants used for 1 hour or less per day electronic devices (see Table 9).

Table 9

Descriptive Statistics for Family Health and Activities – Time spent with electronics

Variable	Frequency	Valid percent
On an average weekday, about how much time does [S.C.] usually spend with computers, cell phones, handheld video games, and other electronic devices, doing things other than schoolwork?		
0-Does not use electronic devices	130	7.9
1-Uses electronic devices 1 hour or less per day	707	42.7
2-Uses electronic devices more than 1 hour but less than 4 hours per day	481	29
3-Uses electronic devices 4 hours or more per day	339	20.5
Missing	30	
Total	1688	

Approximately, 1153 (68.3%) of the participants have electronic devices in the bedroom (see Table 10).

Table 10

Descriptive Statistics for Family Health and Activities – Electronics in the bedroom

Variable	Frequency	Valid percent
Does [he/she] have a TV, computer, or access to electronic devices in [his/her] bedroom?		
0-No	535	31.7
1-Yes	1153	68.3
Total	1688	

Nearly, 453 (27.5%) of the participants reported reading for 1-30 minutes or less on an average weekday (see Table 11).

Table 11

Descriptive Statistics for Family Health and Activities – Time spent reading

Variable	Frequency	Valid percent
On an average weekday, about how much time does [child name] usually spend time reading for pleasure?		
0-None	353	21.4
1-30 minutes or less	453	27.5
2-31 minutes to 1 hour	432	26.2
3-more than 1 hour	412	25
Missing	39	
Total	1688	

Statistical assumptions

The assumptions were evaluated for binary logistic regression analysis. This type of regression does not rely on the assumptions made with linear regression such as linearity, normality, and homogeneity of variance (Mertler & Vannatta, 2013). However, multicollinearity is a key concern for binary logistic regression (Mertler & Vannatta, 2013). To check for multicollinearity among the predictors, tolerance, and variation inflation (VIF) factors was assessed. If the tolerance level exceeds .1 and VIF is less than 10, then multicollinearity is not an issue (Mertler & Vannatta, 2013).

Statistical analysis

Binary logistic regression was used to answer these questions and test the hypotheses. The logistic regressions were done on a weighted basis. The sampling weight variable NSCHWT was used in the study. This ensured that standard errors, significant levels, and confidence intervals would be calculated accurately and not be inflated due to estimated population counts. The researcher may be worried about committing Type I errors when several hypothesis tests are performed (Frane, 2015; Green & Salkind, 2014). If the null hypothesis is rejected when it is true this is known as a Type I error (Frane, 2015; Green & Salkind, 2014). When conducting a hypothesis test it is necessary for the researcher to reduce the probability of committing a Type I error (Frane, 2015; Green & Salkind, 2014). To achieve this the alpha value is set to .05 which means the error could occur less than 5% of the time (Frane, 2015; Green & Salkind, 2014). The findings are organized by research questions and hypotheses.

Research Question(s) and Hypotheses

Research Question 1 (RQ1)

Is there an association between neighborhood safety and support and BMI among 10-17 year olds in Florida and Georgia? Hierarchical binary logistic regression was used to evaluate the impact of various neighborhood safety and support variables (Block 2) on the BMI designation (underweight/healthy or overweight/obese) after controlling for the influence of state (Block 1). The independent variable neighborhood safety and support measure was composed of the following domains which included social capital, perceived safety, neighborhood conditions, and neighborhood amenities. These variables and questions was obtained from the NSCH 2012/2012 data set (DRC, n.d.d.). The neighborhood safety and support independent questions were:

- How often do you feel [S.C.] is safe in your community or neighborhood?
- If my child were outside playing and got hurt or scared, there are adults nearby who I trust to help my child.
- There are people I can count on in this neighborhood.
- We watch out for each other's children in this neighborhood.
- People in this neighborhood help each other out.
- Does a park or playground area exist in your neighborhood?
- Does a recreation center, community center, or boys' or girls' club exist in your community?
- In your neighborhood, is there litter or garbage on the street or sidewalk?
- How about poorly kept or [dilapidated/rundown] housing?

- How about vandalism such as broken windows or graffiti?
- Do sidewalks or walking paths exist in your neighborhood?

Preliminary analyses were conducted to ensure there were no outliers and no multicollinearity problems. No absolute values of Beta > .9 and no Tolerance values < .1 and no VIF values > 10; therefore, no problems with multicollinearity for question 1 (see Table 12). Bivariate analysis was conducted on the dependent and independent variables. This will indicate which independent variables have a major association with the dependent variable. A chi-square test of independence was used to determine if there is a relationship between the variables. The null hypothesis there is no relationship between the independent and dependent variable being tested. The effect size measures (Phi & Cramer's V and Gamma) are used to assess the strength of any significant relationship. For Phi & Cramer's V, a value of 0.10 is weak, 0.30 is medium, and 0.50 is strong. For Gamma, a value of 0.3 is weak, 0.6 is medium, and 0.75 is strong (Green & Salkind, 2014). The chi-square analysis results show several significant variables. "Do sidewalks or walking paths exist in your neighborhood" (K10Q11), was significant, $\chi^2(1, N = 1584) = 16.17, p = .001$. The strength of the association was weak, Cramer's V = 0.10. "How about poorly kept or [dilapidated/rundown] housing" (K10Q22), was significant, $\chi^2(1, N = 1578) = 13.78, p = .001$. The strength of the association was weak, Cramer's V = 0.09. "People in this neighborhood help each other out" (K10Q30), was significant, $\chi^2(3, N = 1557) = 15.16, p = .002$. The strength of the association was weak, Gamma = 0.09.

Table 12

Coefficients for Measuring Multicollinearity for Neighborhood Safety and Support

<i>Model</i>	<i>Unstandardized Coefficients</i>		<i>Standardized Coefficients</i>	<i>Collinearity Statistics</i>	
	<i>B</i>	<i>Std. Error</i>	<i>Beta</i>	<i>Tolerance</i>	<i>VIF</i>
<i>(Constant)</i>	.277	.085			
<i>K10Q30 People in this neighborhood help each other out.</i>	.029	.02	.051	.528	1.89
<i>K10Q31 We watch out for each other's children in this neighborhood.</i>	.002	.021	-.003	.446	2.24
<i>K10Q32 There are people I can count on in this neighborhood.</i>	.013	.022	.025	.378	2.64
<i>K10Q34 If my child were outside playing and got hurt or scared, there are adults nearby who I trust to help my child.</i>	-.013	.022	-.022	.477	2.09
<i>K10Q40 How often do you feel [S.C.] is safe in your community or neighborhood?</i>	.002	.018	.003	.797	1.25
<i>K10Q20 In your neighborhood, is there litter or garbage on the street or sidewalk?</i>	-.025	.041	-.007	.793	1.26
<i>K10Q22 How about poorly kept or [dilapidated/rundown] housing?</i>	.144	.038	.116	.705	1.41
<i>K10Q23 How about vandalism such as broken windows or graffiti?</i>	-0.1	.051	-.058	.751	1.33
<i>K10Q11 Do sidewalks or walking paths exist in your neighborhood?</i>	-.098	.028	-.098	.804	1.24

(table continues)

<i>Model</i>	<i>Unstandardized Coefficients</i>		<i>Standardized Coefficients</i>	<i>Collinearity Statistics</i>	
	<i>B</i>	<i>Std. Error</i>	<i>Beta</i>	<i>Tolerance</i>	<i>VIF</i>
K10Q12 Does a park or playground area exist in your neighborhood?	-.009	.03	-.008	.8	1.25
K10Q13 Does a recreation center, community center, or boys' or girls' club exist in your community?	.04	.027	.041	.88	1.13

Note. a. Dependent Variable: BMI_2groups BMI grouped into 2 groups.

The logistic regression results were used to answer the question. The model fit, classification table, and summary of model variables was used to help determine if the model is a good fit. In the Block 1 model with state only was statistically significant, $\chi^2(1, N = 1688) = 11.09, p = .001$, explaining about 1% of the variance in BMI (see Tables 13 and 14). After adding the Block 2 variables and using backward stepwise selection, and retaining the state IV, the overall model was statistically significant, $\chi^2(6, N = 1688) = 59.13, p < .001$, explaining between 4% and 6% of the variance in BMI (see Tables 15 and 16). The model correctly predicted the BMI classification of 70.3% of the cases.

Table 13

Omnibus Tests of Model Coefficients of Block 1 for Neighborhood Safety and Support

		Chi-square	df	Sig.
Step 1	Step	11.085	1	.001
	Block	11.085	1	.001
	Model	11.085	1	.001

Table 14

Model Summary of Block 1 for Neighborhood Safety and Support

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	1820.624 ^a	.007	.010

Note. a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Table 15

Omnibus Tests of Model Coefficients of Block 2 for Neighborhood Safety and Support

		Chi-square	df	Sig.
Step 1	Step	53.661	21	.000
	Block	53.661	21	.000
	Model	64.745	22	.000
Step 2 ^a	Step	.000	1	.988
	Block	53.661	20	.000
	Model	64.745	19	.000
Step 3 ^a	Step	-.654	3	.884
	Block	53.007	17	.000
	Model	64.091	18	.000
Step 4 ^a	Step	-1.490	3	.685
	Block	51.517	14	.000
	Model	62.601	15	.000
Step 5 ^a	Step	-1.874	3	.599
	Block	49.643	11	.000
	Model	60.727	12	.000
Step 6 ^a	Step	-1.152	3	.765
	Block	48.491	8	.000
	Model	59.576	9	.000
Step 7 ^a	Step	-.450	1	.502
	Block	48.041	7	.000
	Model	59.126	6	.000

Note. a. A negative Chi-squares value indicates that the Chi-squares value has decreased from the previous step.

Table 16

Model Summary of Block 2 for Neighborhood Safety and Support

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	1766.963 ^a	.042	.060
2	1766.964 ^a	.042	.060
3	1767.617 ^a	.042	.059
4	1769.107 ^a	.041	.058
5	1770.982 ^a	.040	.056
6	1772.133 ^a	.039	.055
7	1772.583 ^a	.039	.055

Note. a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Table 17 shows the significant neighborhood safety and support independent variables (IVs) in the final model. The strongest predictor of overweight/obese was “How about poorly kept or [dilapidated/rundown] housing?” with an odds ratio of 1.9. This indicated that those people answering “yes” were almost 2 times more likely to be overweight/obese than those answering “no” when controlling for all other IVs in the model. The weakest predictor of overweight/obese was “People in this neighborhood help each other out.” with those people answering, “somewhat disagree” having an odds ratio of 0.29. This indicated that those people answering, “somewhat disagree” have 70% lower odds to be overweight/obese than those answering, “definitely disagree” when controlling for all other IVs in the model. The odds ratio for state indicated that those people in Georgia were about 1.4 more likely to be overweight/obese than those people in Florida, when controlling for all other IVs in the model.

Table 17

Logistic Regression Predicting Likelihood of being Overweight/Obese based on Neighborhood and Support

Independent Variable	B	Sig.	OR	95% CI	
				Lower	Upper
State (Florida is reference)	.37	.002	1.45	1.15	1.83
Do sidewalks or walking paths exist in your neighborhood?	-.41	.001	.66	.052	.085
How about poorly kept or [dilapidate/rundown] housing?	.66	.001	1.94	1.4	2.69
How about vandalism such as broken windows or graffiti?	-.63	.013	.53	.32	.088
People in this neighborhood help each other out		.001			
Definitely Agree	-.096	.000	.38	.23	.64
Somewhat Agree	-0.9	.000	.41	.25	.68
Somewhat Disagree	-1.25	.000	.29	.15	.54
Constant	-.05	.854	.95		

Note. OR = odds ratio; CI = confidence interval.

When looking at each state separately, only two of the neighborhood safety and support variables were significant for Georgia, while five were significant for Florida. The Block 1 model for Georgia using backward stepwise selection was statistically significant, $\chi^2(3, N = 848) = 26.33, p < .001$, explaining between 5% and 6% of the variance in BMI (see Tables 18 and 19). The model correctly predicted the BMI classification of 67.0% of the cases. For Georgia, “Do sidewalks or walking paths exist in your neighborhood?” and “How about poorly kept or [dilapidated/rundown] housing?” were significant, with those answering “yes” have 40% lower odds of being overweight/obese and the latter increasing the likelihood of being overweight/obese by a factor of 2.65 (see Table 20).

Table 18

Omnibus Tests of Model Coefficients of Neighborhood Safety and Support for Georgia

		Chi-square	df	Sig.
Step 1	Step	37.889	21	.013
	Block	37.889	21	.013
	Model	37.889	21	.013
Step 9 ^b	Step	-1.408	1	.235
	Block	26.334	5	.000
	Model	26.334	3	.000

Table 19

Model Summary of Neighborhood Safety and Support for Georgia

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	700.446 ^b	0.064	0.089
9	712.001 ^b	0.045	0.062

Note. a. STATE = 11. b. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Table 20

Logistic Regression Predicting Likelihood of being Overweight/Obese in Georgia

Independent Variable	B	Sig.	OR	95% CI	
				Lower	Upper
Do sidewalks or walking paths exist in your neighborhood?	-.525	.004	0.592	0.412	0.85
How about poorly kept or [dilapidate/rundown] housing?	.975	.001	2.65	1.59	4.41
Constant	-.298	.067	.743		

Note. OR = odds ratio; CI = confidence interval.

The Block 1 model for Florida using backward stepwise selection model was statistically significant, $\chi^2(5, N = 840) = 43.58, p < .001$, explaining between 5% and 7% of the variance in BMI (see Tables 21 and 22). This was very similar to the overall results. The model correctly predicted the BMI classification of 73.7% of the cases. The strongest indicator of being overweight/obese was “How about poorly kept or [dilapidated/rundown] housing?” with those answering “yes” being 1.6 times more likely of being overweight/obese compared to those answering “no” when controlling for all other IVs in the model. The weakest predictor of overweight/obese was “People in this neighborhood help each other out” with those people answering, “somewhat disagree” having an odds ratio of 0.16. This indicated that those people answering, “somewhat disagree” have 84% lower odds to be overweight/obese than those answering, “definitely disagree” when controlling for all other IVs in the model. The five significant variables are listed in the table (see Table 23). Based on the results of the binary logistic regression, there was evidence to reject the null hypothesis and conclude there is an association between neighborhood safety and support and BMI among 10-17 year olds in Florida and Georgia. The conclusion was the same for Florida and Georgia separately.

Table 21

Omnibus Tests of Model Coefficients of Neighborhood Safety and Support for Florida

		Chi-square	df	Sig.
Step 1	Step	60.363	21	.000
	Block	60.363	21	.000
	Model	60.363	21	.000
Step 7 ^b	Step	-2.664	1	.103
	Block	43.575	7	.000
	Model	43.575	5	.000

Note. a. STATE = 10. b. A negative Chi-squares value indicates that the Chi-squares value has decreased from the previous step.

Table 22

Model Summary of Neighborhood Safety and Support for Florida

1	1021.926 ^b	0.063	0.091
7	1038.714 ^b	0.046	0.067

Note. a. STATE = 10. b. Estimation terminated at iteration number 5 because parameter estimates changes by less than .001.

Table 23

Logistic Regression Predicting Likelihood of being Overweight/Obese in Florida

Independent Variable	B	Sig.	OR	95% CI for OR	
				Lower	Upper
Do sidewalks or walking paths exist in your neighborhood?	-.529	.005	.59	.407	.852
Does a park or playground area exist in your neighborhood?	.482	.022	1.62	1.07	2.44
How about poorly kept or [dilapidate/rundown] housing?	.492	.016	1.64	1.09	2.45
How about vandalism such as broken windows or graffiti?	-1.46	.001	.23	.107	.503
People in this neighborhood help each other out.	-1.87	.001	.16	.07	.37
Constant	.29	.419	1.34		

Note. OR = odds ratio; CI = confidence interval.

Research Question 2 (RQ2)

Is there an association between physical activity and BMI among 10-17 year olds in Florida and Georgia? Hierarchical binary logistic regression was used to evaluate the impact of physical activity (Block 2) on the BMI designation (underweight/healthy or overweight/obese) after controlling for the influence of state (Block 1). This variable and questions was obtained from the NSCH 2012/2012 data set (DRC, n.d.d.). The physical activity independent question was:

- During the past week, on how many days did [child name] exercise, play a sport, or participate in physical activity for at least 20 minutes that made [him/her] sweat and breathe hard?

Preliminary analyses were conducted to ensure there were no outliers.

Multicollinearity is not an issue since there was only one independent variable. Bivariate analysis was conducted on the dependent and independent variables. This will indicate which independent variables have a statistically significant relationship with the dependent variable. A chi-square test of independence was used to determine if there is a relationship between the variables. The null hypothesis there is no relationship between the independent and dependent variable being tested. The chi-square analysis results indicate physical activity variable was not significant, $\chi^2(1, N = 1593) = 4.81, p = .187$. The strength of the association was weak, Gamma = 0.03. The logistic regression results were used to answer the question. The Block 1 model with state only was statistically significant, $\chi^2(1, N = 1688) = 10.65, p = .001$, explaining about 1% of the variance in BMI (see Tables 24 and 25). After adding the Block 2 variable, and retaining the state

IV, the overall model was statistically significant, $\chi^2(4, N = 1688) = 14.51, p = .006$, still explaining only about 1% of the variance in BMI (see Tables 26 and 27). The model correctly predicted the BMI classification of 69.7% of the cases.

Table 24

Omnibus Tests of Model Coefficients of Block 1 for Physical Activity

		Chi-square	df	Sig.
Step 1	Step	10.652	1	.001
	Block	10.652	1	.001
	Model	10.652	1	.001

Table 25

Model Summary of Block 1 for Physical Activity

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	1943.363 ^a	.007	.009

Note. a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Table 26

Omnibus Tests of Model Coefficients of Block 2 for Physical Activity

		Chi-square	df	Sig.
Step 1	Step	3.853	3	.278
	Block	3.853	3	.278
	Model	14.506	4	.006

Table 27

Model Summary of Block 2 for Physical Activity

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	1939.510 ^a	.009	.013

Note. a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Table 28 shows the physical activity independent variable was not significant ($p = .295$). However, state was a significant variable ($p = .002$). The odds ratio for state indicates that those people in Georgia were about 1.4 more likely to be overweight/obese than those people in Florida, when controlling for all other IVs in the model.

Table 28

Logistic Regression Predicting Likelihood of being Overweight/Obese

Independent Variable	B	Sig.	OR	95% CI	
				Lower	Upper
State (Florida is the reference)	.35	.002	1.42	1.14	1.77
During the past week, on how many days did [child name] exercise, play a sport, or participate in physical activity for at least 20 minutes that made [him/her] sweat and breathe hard? (Reference is 0)					
		.295			
1-3 days	.35	.098	1.42	.94	2.14
4-6 days	.37	.060	1.45	.98	2.15
Everyday	.29	.164	1.33	.89	2.00
Constant	-1.28	.000	0.28		

Note. OR = odds ratio; CI = confidence interval.

When looking at each state separately, the model for Georgia was not significant, $\chi^2(3, N = 848) = 3.47, p = .33$ (see Tables 29 and 30). Table 31 shows the likelihood of children becoming obese/overweight in Georgia.

Table 29

Omnibus Tests of Model Coefficients^a of Physical Activity for Georgia

		Chi-square	df	Sig.
Step 1	Step	3.467	3	.325
	Block	3.467	3	.325
	Model	3.467	3	.325

Note. a. STATE = 11

Table 30

Model Summary of Physical Activity for Georgia

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	775.470 ^b	.006	.008

Note. a. STATE = 11. b. Estimation terminated at iteration number 3 because parameter estimates changed by less than .001.

Table 31

Logistic Regression predicting the likelihood of being overweight/obese in Georgia

Independent Variable	B	Sig.	OR	95% CI	
				Lower	Upper
During the past week, on how many days did [child name] exercise, play a sport, or participate in physical activity for at least 20 minutes that made [him/her] sweat and breathe hard? (Reference is 0)		0.33			
1-3 days	-.552	.092	.576	.303	1.09
4-6 days	-.243	.427	.784	.430	1.43
Everyday	-.277	.394	.758	.401	1.43
Constant	-.307	.266	.736		

Note. OR = odds ratio; CI = confidence interval.

The model for Florida was significant, $\chi^2(3, N = 840) = 12.85, p = .005$, explaining about 1% of the variance in BMI (see Tables 32 and 33). Children in Florida having physical activity 1 to 3 days were about 2.6 times more likely to be overweight/obese than those in Florida with no activity. The children in Florida having physical activity 4 to 6 days were about 2.2 times more likely to be overweight/obese than those with no activity, while those having physical activity everyday were about 2 times more likely to be overweight/obese than those with no activity. Thus, as physical activity went up for children in Florida, the likelihood of being overweight/obese went down (see Table 34). Based on the results of the binary logistic regression, when looking at Florida and Georgia combined, since physical activity was not significant, there was no evidence to reject the null hypothesis. The results were the same for Georgia alone.

However, for Florida alone, there was evidence to reject the null hypothesis and conclude there was an association between physical activity and BMI among 10-17 year olds in Florida.

Table 32

Omnibus Tests of Model Coefficients of Physical Activity for Florida

		Chi-square	df	Sig.
Step 1	Step	12.847	3	.005
	Block	12.847	3	.005
	Model	12.847	3	.005

Note. a. STATE = 10

Table 33

Model Summary of Physical Activity for Florida

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	1151.579 ^b	.013	.019

Note. a. STATE = 10. b. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Table 34

Logistic Regression Predicting Likelihood of being Overweight/Obese in Florida

Independent Variable	B	Sig.	OR	95% CI	
				Lower	Upper
During the past week, on how many days did [child name] exercise, play a sport, or participate in physical activity for at least 20 minutes that made [him/her] sweat and breathe hard? (Reference is 0)		.009			
1-3 days	.959	.001	2.61	1.48	4.59
4-6 days	.790	.004	2.20	1.28	3.79
Everyday	.672	.018	1.96	1.12	3.43
Constant	-1.69	.000	.184		

Note. OR = odds ratio; CI = confidence interval.

Research Question 3 (RQ3)

Is there an association between family health and activities and BMI among 10-17 year olds in Florida and Georgia? Hierarchical binary logistic regression was used to evaluate the impact of various family health and activities variables (Block 2) on the BMI designation (underweight/healthy or overweight/obese) after controlling for the influence of state (Block 1). These variables and questions was obtained from the NSCH 2012/2012 data set (DRC, n.d.d.). The family health and activities independent variables were:

- Time spent using electronic devices on an average weekday-- children age 6 to 17 yrs.
- Time spent watching TV or videos on an average weekday-- children age 1 to 17 yrs.
- During the past week, on how many days did all the family members who live in the household eat a meal together?
- On an average weekday, about how much time does [child name] usually spend reading for pleasure?
- Does a recreation center, community center, or boys' or girls' club exist in your community?
- Does [he/she] have a TV, computer, or access to electronic devices in [his/her] bedroom?

Preliminary analyses were conducted to ensure there were no outliers and no multicollinearity problems. No absolute values of Beta $> .9$ and no Tolerance values $< .1$

and no VIF values > 10; therefore, no problems with multicollinearity for question 3 (see Table 35). Bivariate analysis was conducted on the dependent and independent variables. This will indicate which independent variables have a statistically significant association with the dependent variable. A chi-square test of independence was used to determine if there is a relationship between the variables. The null hypothesis there is no relationship between the independent and dependent variable being tested. The chi-square analysis results indicate “Time spent using electronic devices during average weekday” (Ind6_10b11) is significant, $\chi^2(3, N = 1583) = 10.62, p = .014$. The strength of the negative association was weak, Gamma = -0.03. “Time spent watching TV or videos on average weekday” (Ind6_10_11) is significant, $\chi^2(3, N = 1602) = 10.53, p = .015$. The strength of the association was weak, Gamma = 0.14. “On an average weekday, about how much time does [child name] spend reading for pleasure” (Ind5_6_11) was significant, $\chi^2(3, N = 1570) = 8.87, p = .031$. The strength of the negative association is weak, Gamma = -0.06. “Does [he/she] have a TV, computer, or access to electronic devices in [his/her] bedroom” (K7Q62) was significant, $\chi^2(1, N = 1604) = 7.06, p = .008$. The strength of the association was weak, Cramer’s V = 0.07.

Table 35

Coefficients for Measuring Multicollinearity for Family Health and Activities

Model	Unstandardized Coefficients		Standardized Coefficients	Collinearity Statistics	
	B	Std. Error	Beta	Tolerance	VIF
(Constant)	0.182	0.047			
Ind6_8_11 During the past week, how many days did all the family members eat a meal together in the household.	0.027	0.014	0.051	0.96	1.041
Ind6_10_11 Time spent watching TV or videos on average weekday –children age 1 to 17.	0.056	0.015	0.099	0.888	1.126
Ind6_10b_11 Time spent using electronic devices average weekday –children age 6 to 17 years.	-0.023	0.014	-0.044	0.88	1.136
Ind5_6_11 On an average weekday, about how much time does [child name] spend reading for pleasure?	-0.021	0.011	-0.05	0.959	1.043
K7Q62 Does [he/she] have a TV, computer, or access to electronic devices in [his/her] bedroom?	0.06	0.026	0.061	0.962	1.04

Note. a. Dependent Variable: BMI_2groups

The logistic regression results were used to answer the question. The Block 1 model with state only was statistically significant, $\chi^2 (1, N = 1688) = 8.84, p = .003$, explaining about 1% of the variance in BMI (see Tables 36 and 37).

Table 36

Omnibus Tests of Model Coefficients of Block 1 for Family Health and Activities

		Chi-square	df	Sig.
Step 1	Step	8.837	1	.003
	Block	8.837	1	.003
	Model	8.837	1	.003

Table 37

Model Summary of Block 1 for Family Health and Activities

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	1902.475 ^a	.006	.008

Note. a. Estimation terminated at iteration number 3 because parameter estimates changed by less than .001.

After adding the Block 2 variables and using backward stepwise selection, and retaining the state IV, the overall model was statistically significant, $\chi^2 (10, N = 1688) = 39.06, p < .001$, explaining between 2.5% and 3.5% of the variance in BMI. The model correctly predicted the BMI classification of 69.7% of the cases (see Tables 38 and 39).

Table 38

Omnibus Tests of Model Coefficients of Block 2 for Family Health and Activities

		Chi-square	df	Sig.
Step 1	Step	37.870	13	.000
	Block	37.870	13	.000
	Model	46.707	14	.000
Step 2 ^a	Step	-3.129	3	.372
	Block	34.741	10	.000
	Model	43.578	13	.000
Step 3 ^a	Step	-4.521	3	.210
	Block	30.220	7	.000
	Model	39.057	10	.000

Note. a. A negative Chi-squares value indicates that the Chi-squares value has decreased from the previous step.

Table 39

Model Summary of Block 2 for Family Health and Activities

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	1864.605 ^a	.030	.042
2	1867.733 ^a	.028	.039
3	1872.254 ^a	.025	.035

Note. a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Table 40 shows the significant family health and activities IVs in the final model. The strongest predictor of overweight/obese was “Time spent watching TV or videos on an average weekday-- children age 1 to 17 yrs.”, with those people “watching TV \geq 4 hours per day” having an odds ratio of 1.9. This indicated that those people “watching TV \geq 4 hours per day” were about 2 times more likely to be overweight/obese than those “not watching TV” when controlling for all other IVs in the model. The weakest predictor of overweight/obese was “Time spent using electronic devices on an average weekday-- children age 6 to 17 yrs.” with each of the categories having an odds ratio of about 0.50. This indicated that those people answering any usage category have 50% lower odds to be overweight/obese than those “not using electronic devices” when controlling for all other IVs in the model. Again, the odds ratio for state indicates that those people in Georgia were about 1.4 times more likely to be overweight/obese than those people in Florida, when controlling for all other IVs in the model.

Table 40

Logistic Regression Predicting Likelihood of being Overweight/Obese

Independent Variable	B	Sig.	OR	95% CI	
				Lower	Upper
State (Florida is reference)	0.37	.001	1.45	1.16	1.81
Time spent watching TV or videos on average weekday - children age 1 to 17 yrs (Reference is 0)		.005			
Watches TV \leq 1 hour per day	0.12	.668	1.12	0.66	1.92
Watches TV $>$ 1 hour but $<$ 4 hours per day	0.43	0.11	1.53	0.91	2.59
Watches TV \geq 4 hours per day	0.67	0.02	1.96	1.11	3.45
Time spent using electronic devices on average weekday—children age 6 to 17 yrs (Reference 0)		.008			
Uses Electronic Devices \leq 1 hour per day	-0.68	.001	0.5	0.33	0.76
Uses Electronic Devices $>$ 1 but $<$ 4 hours per day	-0.69	.002	0.5	0.32	0.77
Uses Electronic Devices \geq 4 hours per day	-0.73	.002	0.48	0.3	0.77
Does [he/she] have a TV, computer, or access to electronic devices in [his/her] bedroom?	0.34	.006	1.41	1.1	1.81
Constant	-0.91	.002	0.4		

Note. OR = odds ratio; CI = confidence interval.

When looking at each state separately, only two of the family health and activities variables were significant for Georgia, while three were significant for Florida. The Georgia model was significant, $\chi^2(9, N = 848) = 34.86, p < .001$, explaining about 1% of the variance in BMI (see Tables 41 and 42). For Georgia, two IVs were significant: “Time spent using electronic devices on average weekday-- children age 6 to 17 yrs ($p = .007$).” In this case, the overall IV was significant but none of the individual categories were significant, when controlling for all other IVs in the model. “On an average weekday, about how much time does [child name] usually spend reading for pleasure” ($p = .012$). Only the middle category, “31 mins. to 1 hour”, was significant and had an odds ratio of .51, indicating those “spending 31 mins. to 1 hour reading for pleasure” have 49% lower odds to be overweight/obese than those “not reading for pleasure” when controlling for all other IVs in the model (see Table 43).

Table 41

Omnibus Tests of Model Coefficients of Family Health and Activities for Georgia

		Chi-square	df	Sig.
Step 1	Step	36.848	13	.000
	Block	36.848	13	.000
	Model	36.848	13	.000
Step 2 ^b	Step	-1.124	3	.771
	Block	35.724	10	.000
	Model	35.724	12	.000
Step 3 ^b	Step	-.861	1	.353
	Block	34.862	9	.000
	Model	34.862	9	.000

Note. a. STATE = 11. b. A negative Chi-squares value indicates that the Chi-squares value has decreased from the previous step.

Table 42

Model Summary of Family Health and Activities for Georgia

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	729.247 ^b	.060	.083
2	730.371 ^b	.059	.081
3	731.233 ^b	.057	.079

Note. a. STATE = 11. b. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Table 43

Logistic Regression Predicting Likelihood of being Overweight/Obese in Georgia

Independent Variable	B	Sig.	OR	95% CI	
				Lower	Upper
Time spent using electronic devices average weekday—children age 6 to 17 yrs (Reference 0)		.007			
Uses Electronic Devices ≤ 1 hour per day	-.06	.874	.95	.48	1.85
Uses Electronic Devices > 1 but < 4 hours per day	-.17	.631	.84	.42	1.69
Uses Electronic Devices ≥ 4 hours per day	.66	.078	1.93	.93	4.02
On average weekday, about how much time does [child name] usually spend reading for pleasure?		.012			
1 = 30 minutes or less	.02	.922	1.02	.63	1.66
2 = 31 minutes to 1 hour	-.67	.012	.51	.31	0.86
3 = more than 1 hour	-.50	.053	.61	.36	1.01
Constant	-.90	.066	.41		

Note. OR = odds ratio; CI = confidence interval.

The Florida model was significant, $\chi^2(9, N = 840) = 42.8, p < .001$, explaining about 1% of the variance in BMI (see Tables 44 and 45). For Florida, three IVs were significant: “Time spent watching TV or videos on average weekday-- children age 1 to 17 yrs.” ($p = .008$). Only the last category, those people “watching TV ≥ 4 hours per day” was significant and had an odds ratio of 2.4, indicating those “watching TV ≥ 4 hours per day” were about 2.4 times more likely to be overweight/obese than those “not watching TV” when controlling for all other IVs in the model. “Time spent using electronic devices average weekday-- children age 6 to 17 yrs.” ($p < .001$). The last category, “using electronic devices ≥ 4 hours per day” was significant with an odds ratio of .16, indicating children “using electronic devices ≥ 4 hours per day” have 85% lower odds to be overweight/obese than those “not using electronic devices” when controlling for all other IVs in the model. The odds ratio was low and this may be due to parents self-reporting incorrect information on the number hours their child used electronic devices. Also, a small or a large odds ratio may be significant or not significant, depending on the sample size and the value of the reference category. The sample size for this study was small. The other 2 categories have 65% lower odds to be overweight/obese. “Does [he/she] have a TV, computer, or access to electronic devices in [his/her] bedroom?” ($p < .033$) with an odds ratio of 1.44. This indicated that those people answering “yes” were about 1.4 times more likely to be overweight/obese than those answering “no” when controlling for all other IVs in the model (see Table 46). Based on the results of the binary logistic regression, there was evidence to reject null hypothesis and conclude there is an association between family health and activities and

BMI among 10-17 year olds in Florida and Georgia. The conclusion was the same for Florida and Georgia separately.

Table 44

Omnibus Tests of Model Coefficients of Family Health and Activities for Florida

		Chi-square	df	Sig.
Step 1	Step	46.736	13	.000
	Block	46.736	13	.000
	Model	46.736	13	.000
Step 2 ^b	Step	-1.383	3	.709
	Block	45.353	10	.000
	Model	45.353	12	.000
Step 3 ^b	Step	-2.556	3	.465
	Block	42.796	7	.000
	Model	42.796	9	.000

Note. a. STATE = 10. b. A negative Chi-squares value indicates that the Chi-squares value has decreased from the previous step.

Table 45

Model Summary of Family Health and Activities for Florida

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	1089.644 ^b	.048	.069
2	1091.027 ^b	.046	.067
3	1093.583 ^b	.044	.063

Note. a. STATE = 10. b. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Table 46

Logistic Regression Predicting Likelihood of being Overweight/Obese in Florida

Independent Variable	B	Sig.	OR	95% CI for OR	
				Lower	Upper
Time spent watching TV or videos on average weekday—children age 1 to 17 yrs		.008			
Watches TV \leq 1 hour per day	.16	.686	1.17	.54	2.54
Watches TV $>$ 1 hour but $<$ 4 hours per day	.59	.122	1.82	.85	3.88
Watches TV \geq 4 hours per day	.87	.036	2.40	1.06	5.39
Time spent using electronic devices average weekday—children age 6 to 17 yrs		.000			
Uses Electronic Devices \leq 1 hour per day	-1.09	.000	.34	.19	.58
Uses Electronic Devices $>$ 1 but $<$ 4 hours per day	-1.02	.001	.36	0.2	.64
Uses Electronic Devices \geq 4 hours per day	-1.83	.000	.16	.08	.31
Does [he/she] have a TV, computer, or access to electronic devices in [his/her] bedroom					
Yes	.36	.033	1.44	1.03	2.01
Constant	-.59	.136	.557		

Note. OR = odds ratio; CI = confidence interval.

Research Question 4 (RQ4)

Is there an association between sociodemographic and BMI among 10-17 year olds in Florida and Georgia? Hierarchical binary logistic regression was used to evaluate the impact of various sociodemographic variables (Block 2) on the BMI designation (underweight/healthy or overweight/obese) after controlling for the influence of state (Block 1). These variables and questions was obtained from the NSCH 2012/2012 data set (DRC, n.d.d.). The sociodemographic independent variables were:

- Race/Ethnicity
- Sex of the selected child
- Poverty level of this household based on DHHS guidelines - Imputed; single imputation using version 3; recoded into 4 categories.
- What is the highest grade or year of school [you have / [S.C.]'s [FATHER TYPE] has] completed?
- What is the highest grade or year of school [you have / [S.C.]'s [MOTHER TYPE] has] completed?
- Family structure, recoded at NCHS, revised version based on PUF 3-20-2009
- Age groups between 10 and 17 years old

Preliminary analyses were conducted to ensure there were no outliers and no multicollinearity problems. No absolute values of Beta > .9 and no Tolerance values < .1 and no VIF values > 10; therefore, no problems with multicollinearity for question 4 (see Table 47). Bivariate analysis was conducted on the dependent and independent variables. This will indicate which independent variables have a statistically significant relationship

with the dependent variable. A chi-square test of independence was used to determine if there is a relationship between the variables. The null hypothesis there is no relationship between the independent and dependent variable being tested. The chi-square analysis results indicate several significant variables. Race/ethnicity was significant, $\chi^2(3, N = 1570) = 39.52, p = .001$. The strength of the association was weak, Cramer's V = 0.16. Family structure was significant, $\chi^2(3, N = 1592) = 9.22, p = .026$. The strength of the association was weak, Cramer's V = 0.08. Sex of child is significant, $\chi^2(1, N = 1605) = 6.12, p = .013$. The strength of the association was weak, Cramer's V = 0.06. Age of group is significant, $\chi^2(1, N = 1605) = 1605, p = .001$. The strength of the association was weak, Cramer's V = 0.09. Poverty level was significant, $\chi^2(3, N = 1606) = 53.46, p = .001$. The strength of the negative association was weak, Gamma = -0.29. Highest grade completed by mother was significant, $\chi^2(2, N = 1396) = 50.18, p = .001$. The strength of the negative association was weak, Gamma = -0.36. Highest grade by father was significant, $\chi^2(2, N = 1085) = 33.64, p = .001$. The strength of the negative association was weak, Gamma = -0.31.

Table 47

Coefficients for Measuring Multicollinearity for Sociodemographic

Model		Unstandardized Coefficients		Standardized Coefficients	Collinearity Statistics	
		B	Std. Error	Beta	Tolerance	VIF
1	(Constant)	0.856	0.104			
	Race4_11 Race/ethnicity	-0.002	0.019	-0.003	0.936	1.068
	Famstruct_11 Family structure	0.018	0.038	0.015	0.96	1.042
	Sex_11 Sex of selected child	-0.081	0.028	-0.089	0.992	1.008
	Povlev4_11 Poverty level	-0.068	0.017	-0.15	0.705	1.418
	EDUC_MOMR	-0.053	0.029	-0.079	0.528	1.893
	EDUC_DADR	-0.029	0.029	-0.043	0.524	1.908

The logistic regression results were used to answer the question. The Block 1 model with state only was not statistically significant, $\chi^2(1, N = 1688) = 0.60, p = .438$, explaining about 1% of the variance in BMI (see Tables 48 and 49).

Table 48

Omnibus Tests of Model Coefficients of Block 1 for Sociodemographic

		Chi-square	df	Sig.
Step 1	Step	.601	1	.438
	Block	.601	1	.438
	Model	.601	1	.438

Table 49

Model Summary of Block 1 for Sociodemographic

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	1200.615 ^a	.001	.001

Note. a. Estimation terminated at iteration number 3 because parameter estimates changed by less than .001.

After adding the Block 2 variables and using backward stepwise selection, and retaining state, the overall model was statistically significant, $\chi^2(9, N = 1688) = 85.34, p < .001$, explaining between 8% and 12% of the variance in BMI. The model correctly predicted the BMI classification of 73.7% of the cases (see Tables 50 and 51).

Table 50

Omnibus Tests of Model Coefficients of Block 2 for Sociodemographic

		Chi-square	df	Sig.
Step 1	Step	87.402	13	.000
	Block	87.402	13	.000
	Model	88.003	14	.000
Step 2 ^a	Step	-.002	1	.963
	Block	87.400	12	.000
	Model	88.001	12	.000
Step 3 ^a	Step	-.732	2	.694
	Block	86.668	10	.000
	Model	87.269	11	.000
Step 4 ^a	Step	-1.933	1	.164
	Block	84.736	9	.000
	Model	85.336	9	.000

Table 51

Model Summary of Block 2 for Sociodemographic

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	1113.213 ^a	.085	.121
2	1113.215 ^a	.085	.121
3	1113.947 ^a	.084	.120
4	1115.880 ^a	.082	.117

Note. a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Table 52 shows the significant sociodemographic IVs in the final model. State was not significant ($p = .289$) for RQ4, indicating that people from Georgia were no more or less likely to be in the overweight/obese BMI category than people from Florida. For Race/Ethnicity: the “Black, non-Hispanic” category was significant ($p < .001$), with an odds ratio of 2.0. This indicates that being in the “Black, non-Hispanic” category increased the likelihood of being in the overweight/obese BMI category by a factor of about 2 compared to those in the “White, non-Hispanic” category, when controlling for all other IVs in the model. The “Hispanic” category was significant ($p = .003$), with an odds ratio of 1.82. This indicates that being in the “Hispanic” category increased the likelihood of being in the overweight/obese BMI category by a factor of about 1.8 compared to those in the “White, non-Hispanic” category, when controlling for all other IVs in the model. The “Multi-racial/Other, non-Hispanic” category was not significant ($p = .368$), which means those in the “Multi-racial/Other, non-Hispanic” category were no more or less likely to be in the overweight/obese BMI category than people in the “White, non-Hispanic” category.

Sex of selected child was significant ($p = .001$), with an odds ratio of .61. This indicated that female selected children have 39% lower odds to be in the overweight/obese BMI category than male selected children, when controlling for all other IVs in the model. For Poverty Level of the Household: The “100-199% FPL” category was significant ($p = .006$), with an odds ratio of .49. This indicated that being in the “100-199% FPL” category children have 51% lower odds of being in the overweight/obese BMI category compared to those in the “0-99% FPL” category, when

controlling for all other IVs in the model. The “200-399% FPL” category was significant ($p = .002$), with an odds ratio of .43. This indicated that being in the “200-399% FPL” category children have 57% lower odds of being in the overweight/obese BMI category compared to those in the “0-99% FPL” category, when controlling for all other IVs in the model. The “400% FPL or greater” category was significant ($p < .001$), with an odds ratio of .31. This indicates that being in the “400% FPL or greater” category children have 69% lower odds of being in the overweight/obese BMI category compared to those in the “0-99% FPL” category, when controlling for all other IVs in the model.

For “What is the highest grade...Mother completed?”: the “High School graduate” category was not significant ($p = .562$), which indicated that those in the “High School graduate” category was no more or less likely to be in the overweight/obese BMI category than those in the “less than High School” category. The “More than High School” category was significant ($p = .033$), with an odds ratio of .57. This indicated that being in the “More than High School” category children have 43% lower odds of being in the overweight/obese BMI category compared to those in the “less than High School” category, when controlling for all other IVs in the model. Based on the results of the binary logistic regression, there was evidence to reject the null hypothesis and conclude there is an association between sociodemographic variables and BMI among 10-17 year olds in Florida and Georgia. There was not a significant difference between Florida and Georgia for RQ4.

Table 52

Logistic Regression Predicting Likelihood of being Overweight/Obese

Independent Variable	B	Sig.	OR	95% CI for OR	
				Lower	Upper
State (Florida is reference)	0.16	0.289	1.18	1.18	1.59
Race/Ethnicity (Reference is White, non-Hispanic)		0			
Black, non-Hispanic	0.72	0	2.05	1.42	2.98
Hispanic	0.6	0.003	1.82	1.23	2.7
Multi-racial/Other, non- Hispanic	-0.32	0.368	0.73	0.36	1.45
Sex of selected child (Reference is Male)	-0.49	0.001	0.61	0.46	0.82
Poverty level of this household based on DHHS guidelines		0.000			
100-199% FPL	-0.71	0.006	0.49	0.3	0.81
200-399% FPL	-0.84	0.002	0.43	0.26	0.73
400% FPL or greater	-1.16	0	0.31	0.18	0.54
What is the highest grade or year of school [you have/[S.C.]'s [Mother Type] has] completed? Reference is less than HS)		0.027			
High School graduate	-0.16	0.562	0.85	0.5	1.45
More than High School	-0.56	0.033	0.57	0.34	0.96
Constant	0.24	0.415	1.27		

Note. OR = odds ratio; CI = confidence interval.

Summary

The objective of this quantitative study was to examine associations between independent variables: neighborhood safety and support, physical activity, family health and activities, sociodemographic on the dependent variable BMI. The sample population consisted of children and adolescents aged 10 to 17 years living in Florida and Georgia. Descriptive statistics and logistic regression models was used to answer the four proposed research questions. Based on the logistic regression results there was an association between neighborhood safety and support, family health and activities, and sociodemographic variables and BMI. The results provided evidence to reject the null hypothesis for these independent variables but not for physical activity. In addition, significant differences were found between Florida and Georgia for neighborhood safety and support, physical activity, and family and health activities. There was no significant difference between Florida and Georgia on sociodemographic factors and BMI.

In the first research question, social capital, neighborhood conditions, and neighborhood amenities domains was significant. The strongest predictor of overweight/obese was “How about poorly kept or [dilapidated/rundown] housing?” “People in this neighborhood help each other out” was the weakest predictor of overweight/obese. Children in Georgia was 1.4 more likely to be obese/overweight than those in Florida. Only two of the neighborhood safety and support variables was significant in Georgia, whereas, five were significant in Florida. For this question, there is evidence to reject the null hypothesis and conclude there was an association between neighborhood safety and support and BMI among 10 to 17 year olds in Florida and

Georgia. The second research question indicated physical activity was not significant, but state was a significant variable. Children in Georgia was about 1.4 times more likely to be overweight/obese than those in Florida. When looking at Florida and Georgia combined physical activity was not significant, thus, no reason to reject the null hypothesis. In Florida, there was evidence to reject the null hypothesis and conclude there was an association between physical activity and BMI.

The third research question showed the strongest predictor of overweight/obese was “Time spent watching TV or videos on an average weekday—children age 1 to 17 yrs ” with children “watching TV \geq 4 hours per day” were about 2 times more likely to be overweight/obese than children “not watching TV”. “Time spent using electronic devices on an average weekday—children age 6 to 17 yrs” was the weakest predictor of overweight/obese with each of the categories having an odds ratio of 0.50. This indicated that those children using electronics have 50% lower odds to be overweight/obese than those “not using electronic devices.” While looking at each state separately, only two of the family health and activities variables was significant in Georgia, while three was significant for Florida. Based on the results there was evidence to reject the null hypothesis and conclude there was an association between family health activities and BMI.

The fourth question indicated race/ethnicity, sex of child, poverty level, and education level was significant. Black, non-Hispanic children and being a female increased the likelihood of being overweight/obese category. A mother that completed more than high school decreased the likelihood of their children being in the

overweight/obese category. Based on the findings there was evidence to reject the null hypothesis and conclude there was an association between sociodemographic variables and BMI. There was not a significant difference between Florida and Georgia. Section 4 included an interpretation of the findings, limitations of the study, recommendations, and implications for professional practice and social change. The conclusion wrap-up the core of the study.

Section 4: Professional Practice and Implications for Social Change

Introduction

The purpose of this quantitative study is to test for significant state differences in childhood obesity prevalence in the South region of the United States. The goal was to examine whether there was association between neighborhood safety and support, physical activity, family health and activities, sociodemographics, and BMI among 10-17 year olds in Florida and Georgia. Section 4 presents the interpretation of the findings, limitations of the study, recommendations for future studies, and implications for professional practices as well social change. A summary of the main results is provided. The data showed there were significant differences between neighborhood safety and support and BMI. Out of the 11 predictor variables, four were statistically significant as well as the state variable. The strongest predictor of overweight obesity was the variable “How about poorly kept or [dilapidated/rundown] housing?” with participants answering “yes” to this question (*OR* 1.94, 95% CI: 1.40, 2.69). The weakest predictor was the variable “People in this neighborhood help each other out” with participants answering, “somewhat disagree” to this question (*OR* 0.29, 95% CI: 0.15, 0.54).

The odds ratio for state indicated that children in Georgia were 1.4 times more prone to be overweight/obese than children in Florida, when controlling for all other IVs in the model (*OR* 1.45, 95% CI: 1.15, 1.83). While looking at each state separately, only two of the neighborhood safety and support variables were significant for Georgia compared to five for Florida. There was evidence to conclude there is an association between neighborhood safety and support and BMI among 10-17 year olds in Florida and

Georgia. The conclusion was the same for Florida and Georgia separately. The data showed no significant differences between physical activity and BMI. Although, the state variable was significant. The odds ratio for state indicates that those people in Georgia were about 1.4 times more likely to be overweight/obese than children in Florida, when controlling for all IVs in the model (*OR* 1.42, 95% CI: 1.14, 1.77). When looking at each state separately, the model for Florida was significant but not Georgia. As physical activity went up for children in Florida, the likelihood of being overweight/obese went down. Based on the findings, physical activity was not significant for Florida and Georgia combined. However, for Florida alone, there was an association between physical activity and BMI among 10-17 year olds.

The data showed there was an association between family health and activities and BMI. Overall, three of the six predictors were statistically significant. The strongest predictor of overweight/obese was “Time spent watching TV or videos on an average weekday—children age 1 to 17 yrs.” Thus, children “watching TV \geq 4 hours per day” were about 2 times more likely to be overweight/ obese than children “not watching TV” (*OR* 1.96, 95% CI: 1.11, 3.45). “Time spent using electronic devices on an average weekday—children age 6 to 17 yrs” was the weakest predictor of overweight/obese, with each of the categories having an odds ratio of about 0.50. This means that those individuals answering any usage category have 50% lower odds to be overweight/obese than those “not using electronic devices” when controlling for all other IVs in the model. The odds ratio for state indicated that those children residing in Georgia were about 1.4 times more likely to be overweight/obese than children in Florida (*OR* 1.45, 95% CI:

1.16, 1.81). When looking at each state separately, only two of the family health and activities variables were significant for Georgia compared to three for Florida. The one variable that both states shared was “Time spent using electronic devices on average weekday—children age 6 to 17 yrs.” Based on the results there was an association between family health activities and BMI among 10-17 year olds in Florida and Georgia. The conclusion was the same for Florida and Georgia separately.

The data showed an association between sociodemographics and BMI. Approximately, four of the seven predictors were statistically significant. Black, non-Hispanic children were more prone to be overweight/obese compared to White, non-Hispanic children (*OR* 2.05, 95% *CI*: 1.42, 2.98). Hispanic children were more likely to be overweight/obese compared to White, non-Hispanic (*OR* 1.82, 95% *CI*: 1.23, 2.70). Multiracial/other children were no more or less likely to be overweight/obese than White, non-Hispanic children. Females were less likely to be overweight/compared to males (*OR* 0.61, 95% *CI*: 0.46, 0.82). When looking at it by state, the results were not significant. Children from Georgia were no more or less likely to be overweight/obese than children from Florida (*OR*, 1.18, 95% *CI*: 1.18, 1.59). All the poverty levels of the household were significant. A parent with “High School” degree was not significant (*OR* 0.85, 95% *CI*: 0.50, 1.45). The parent with an education of “more than High School” was significant (*OR* 0.57, 95% *CI*: 0.34, 0.96) and their children have 43% lower odds of being in the overweight/obese category compared to those with “less than High School” degree. Based on the results there was an association between sociodemographic variables and BMI among 10-17 year olds in Florida and Georgia. There was not a

significant difference between Florida and Georgia. This concludes the summary of the findings.

Interpretation of the Findings

When looking at Florida and Georgia, the findings provided evidence to reject the null hypotheses for Research Questions 1, 3, and 4. Although, there was no evidence to reject the null hypotheses for Research Question 2. Significant differences were found between Florida and Georgia for Research Questions 1, 2, and 3, with evidence to reject the corresponding null hypotheses for each state separately. There was no significant difference between Florida and Georgia for Research Question 4. The purpose of Research Question 1 was to determine if there was an association between neighborhood safety and support and BMI. The literature revealed numerous factors can impact childhood obesity. Prior research studies showed a statistically significant positive link between children BMI and built environment (Taylor et al., 2014). Another study showed litter, noise, and trash was associated with obesity in children aged 3-12 years old (Taylor et al., 2014). Kirby et al. (2012) suggested the built environment, as well as community characteristics, related to racial/ethnic composition may have a significant effect on the weight status of people. In my study, the results indicated neighborhood conditions were the strongest predictor of overweight/obese. The poorly kept housing variable was a strong predictor with children being 2 times more likely to be overweight/obese. Both Georgia and Florida were significant in relation to neighborhoods with poorly kept housing. Social capital was the weakest predictor. The parents answered, "somewhat disagree" that people in the neighborhood help each other

out. These children have 70% lower odds to be overweight/obese than parents answering, “definitely disagree” to the question. There was no association with perceived safety in the community or neighborhood.

A few studies showed neighborhood amenities linked to a reduced risk of overweight or obesity while others found no statistically significant relationship (Duke et al., 2012; Fan & Jin, 2013; Rahman et al., 2011). In this study, there was a significant association between neighborhood amenities and BMI. When looking at each state separately, the existence of sidewalks or walking paths were significant in Georgia. By having sidewalks or walking paths in the neighborhood, these children have 40% lower odds of being overweight/obese. Overall, children in Georgia were 1.4 times more likely to be overweight/obese than children in Florida (*OR* 1.45, 95% CI: 1.15, 1.83). Children in Georgia were 2.6 times more likely to be overweight/obese (*OR* 2.65, 95% CI: 1.59, 4.41), and in Florida 1.6 times, due to poorly kept housing in the neighborhood (*OR* 1.64, 95% CI: 1.09, 2.45). These findings supported previous studies in the literature.

The purpose of Research Question 2 was to determine if there was an association between physical activity and BMI. Children that live in poor neighborhoods within urban, rural, or suburban areas may have a difficult time playing outside without the supervision and protection of a parent or adult present (Guinhouya, 2012; Milteer et al., 2012). There was no association between physical activity and BMI in general, but for state it was significant. In Georgia, children were 1.4 times more likely to be overweight/obese compared to children in Florida (*OR* 1.42, 95% CI: 1.14, 1.77). As

physical activity went up for children in Florida, the likelihood of being overweight/obese decreased.

According to Maher et al. (2012), a high amount of screen time and low physical activity was linked to children being overweight. The purpose of Research Question 3 was to determine if there was an association between family health and activities and BMI. Time spent watching television, video games, or videos are possible risk factors that can lead to childhood obesity (Prentice-Dunn & Prentice-Dunn, 2012; Wethington et al., 2013). Some studies found sedentary behaviors to be linked to overweight or obese when using electronic devices (Prentice-Dunn & Prentice-Dunn, 2012; Wethington et al., 2013). Based on the results, children that watch TV ≥ 4 hours per day were 2 times more likely to be overweight/obese (*OR* 1.96, 95% CI: 1.11, 3.45) in Georgia. This was the strongest predictor of overweight/obese; time spent using electronics was the weakest predictor. Overall, children in Georgia were 1.4 times more likely to be overweight/obese than children in Florida (*OR* 1.45, 95% CI: 1.16, 1.81). In Georgia, time spent watching TV was significant but not the individual categories. Children that read for pleasure for 31 minutes to 1 hour have 49% lower odds to be overweight/obese in Georgia. Also, in Florida, children using electronic devices ≥ 4 hours per day have 84% lower odds to be overweight/obese than those not using electronics. Children watching TV ≥ 4 hours per day were 2.4 more likely to be overweight/obese in Florida (*OR* 2.40, 95% CI: 1.06, 5.39). In Florida, children with BTV were 1.4 times more likely to be overweight/obese (*OR* 1.44, 95% CI: 1.03, 2.01). These findings supported previous studies that showed a positive link with TV viewing time and placing a TV

inside the bedroom as a risk factor for childhood obesity (Sisson et al.; Wethington et al., 2013).

Prior research studies found characteristics like race/ethnicity, age, physical activity, poverty, and sex can impact obesity and neighborhood and safety (Borrell, Graham, & Joseph, 2016). The purpose of Research Question 4 was to determine if there was a relationship between sociodemographic and BMI. Obesity rates and body weights vary across racial and ethnic groups (Frederick et al., 2014; Kirby et al., 2012). According to Martinson et al. (2012), minority status was linked to an increased rate of becoming of overweight. In this study, race/ethnicity was significant. Black, non-Hispanic children were more prone to be overweight/obese followed by Hispanic and Multiracial/Other, non-Hispanic children. The prevalence of overweightness and obesity was seen among girls compared to boys. Obesity rates were the highest among Black males and females than non-Hispanic White males and females (Sen & Patel-Dovlatabadi, 2012; van Vliet et al., 2015). This study indicated that female children have 39% lower odds to be overweight/obese than male children of the same age.

Several research studies showed an association between low SES and obesity among children and adolescent living in developed countries (Kachi et al., 2015). Children of parents with a low income of 100-199% FPL have 51% lower odds of being in the overweight/obese category compared to those with a very low income of 0-99% FPL. The parents that reported a median income of 200-399% FPL have children with 57% lower odds of being in the overweight/obese category compared to those with a very low income of 0-99% FPL. By having parents with a higher income of 400% FPL or

greater, these children have 69% lower odds of being in the overweight/obese category compared to those with a very low income of 0-99% FPL. When it comes to education and income, there are racial and ethnic differences. Based on previous studies, obesity among adolescents have either increased, decreased, or stayed the same over time (Frederick et al., 2014; Kirby et al., 2012, Sen & Patel-Dovlatabadi, 2012). The education level of parents can play a factor in childhood obesity.

Children whose parents had less than a high school education are more likely to be overweight compared to those whose parents had a college degree. The rates of obesity among adolescents whose parents have college degrees decreased and increased among those without a degree (Frederick et al., 2014; Kachi et al., 2015). In this study, when parents had completed high school their children were no more or less likely to be overweight/obese than parents with less than a high school degree. Parents with more than a high school degree had children with 43% lower odds of being overweight/obese compared to parents with less than a high school degree. Overall, the results of this study confirmed what has been found in the literature. Factors such as neighborhood safety and support, physical activity, family health and activities, and sociodemographic are linked to childhood obesity. Also, the state of residence can impact childhood obesity rates. Children in Georgia were more likely to be overweight/obese than in Florida.

The findings from this study are align with the SCT environmental factors that can influence human behavior and the physical environment include having access to healthy foods and opportunities for physical activities (Berlin et al., 2013; Glanz et al., 2015; Nyberg et al., 2011). The role of parents in the social environment is critical for

children to be physically active and adapt to healthy eating habits (Berlin et al., 2013; Glanz et al., 2015; Nyberg et al., 2011). One of the main constructs in SCT is self-efficacy (Glanz et al., 2015). Children watching ≥ 4 hours per day of TV was significant in this study. These children are 2 times more likely to be overweight/obese than those not watching TV. Parental self-efficacy is needed to monitor the number of hours children watch TV to reduce childhood obesity. Environmental factors were significant in this study. The neighborhood condition (poorly kept housing) was the strongest predictor of children being overweight/obese in Florida and Georgia. If the neighborhood is unsafe and in poor conditions these factors limit children being physically active.

Physical activity was significant for children in Florida. The more days the child participated in a physical activity, the less likely they were of being overweight/obese. Behavioral change is important when it comes to monitoring what you eat and being physically active (Philanthropic Collaborative for a Healthy Georgia, 2011). It is important that parents be role models to their kids when observing these particular behaviors. Also, instead of concentrating solely on changing the individual behavior, the aim needs to be mainly on changing policies and the environments at social levels (Philanthropic Collaborative for a Healthy Georgia, 2011).

To combat childhood obesity, it is vital that preventive efforts target low income neighborhoods and racial/ethnic minorities. This is necessary to enable shifts in environmental strategies and behavioral patterns among adolescents at greater risk of becoming overweight (Wang et al., 2011). Based on the results, childhood obesity is

prevalent in the South. This study supports the literature concerning how obesity is impacted by neighborhood safety, physical activity, family health and activities, and sociodemographics.

Limitations of the Study

There are some limitations in this study. First, the use of cross-sectional analyses reduces the researcher ability to make casual inferences. Second, the child's BMI was self-reported by the parents and calculated using weight and height. Thus, the BMI values may not be precise and might lead to reporting bias. Third, the data is from two southern states and the findings may not be generalized to the entire country (Fan & Chen, 2012; Seo & Lee, 2012; Zilanawala et al., 2015).

Recommendations

Further research is essential to combat childhood obesity in the South (Meyers et al., 2015). The findings from this study showed significant state differences in childhood obesity in Florida and Georgia. Overall, the results indicated children in Georgia were more likely to be overweight/obese than in Florida. Georgia ranked third compared to other states with higher rates of overweight/obese in 10 to 17 year olds reported by the Trust for America's Health (Philanthropic Collaborative for a Healthy Georgia, 2011). Prior studies showed neighborhood safety to be linked to higher rates of children being overweight/obese (Borrell, Graham, & Joseph, 2016; Taylor et al, 2014).

In both states neighborhood conditions and neighborhood amenities were significant. Children living in Florida and Georgia with neighborhoods that are poorly kept or rundown increased their chances of being overweight/obese. This condition was

higher among children in Georgia than Florida. In Georgia, having sidewalks or walking paths in neighborhood was significant which decreased the likelihood of children being overweight/obese. The results showed children watching TV ≥ 4 hours per day and placing a TV inside the bedroom was linked with overweight/obese in Florida. These findings build upon previous research studies addressing excessive screen time and TV in bedroom (Maher et al., 2012; Melkevik et al., 2015; Sisson et al., 2011; Wethington et al., 2013). This supports previous research studies that children in the South region were more likely to be overweight or obese and have a TV in the bedroom (Dixon et al., 2012; Sisson et al., 2011).

In the South childhood obesity rates was higher among racial and ethnic minorities (Holt et al., 2011; Trust for America's Health, 2014). In this study, Black, non-Hispanic children followed by Hispanic children had higher rates of BMI compared to White, non-Hispanic children. These findings are consistent with prior research studies on racial/ethnic disparities in obesity (Kirby et al., 2012). There were differences in obesity rates and parental education. In this study, parents with more than a high school degree decreased the likelihood of their children being overweight/obese. This supports prior studies linking overweight and SES (Frederick et al., 2014; Kachi et al., 2015; Zilanawala et al., 2015). Childhood obesity rates were higher among children residing in household with a poverty level of 0-99% FPL. These children were 2 times more likely to be obese than children living in household with poverty level at 400% FPL or greater (Borrell et al., 2016; Kachi et al, 2015). This study results supports these findings.

Gender differences exist in childhood obesity. The results indicated females were less likely to be overweight/obese than males. Sen and Patel-Dovlatabadi (2012) reported African American males had higher rates of obesity compared to non-Hispanic White males. Additional research is essential to explore the different aspects that lead to racial/ethnic and socioeconomic disparities in children that are overweight or obese. Public health programs and policy interventions can assist with controlling these differences in childhood obesity (Martinson et al., 2012). Longitudinal studies on childhood obesity are needed since there are a limited number of studies (Elbel, Corcoran, & Schwartz, 2016).

Implications for Professional Practice and Social Change

It is imperative that community leaders and policy makers collaborate to make neighborhoods safe a top priority for children can play. To control the childhood obesity epidemic there needs to be a continuous change in societal norms (Milteer et al., 2012; Whitaker, 2011). Through positive social change pediatricians can be more involved in creating strategies to prevent the cause instead of treating socially-determined health problems in children. Health professionals can have a significant role in promoting children receive play time at schools, communities, and homes. Pediatricians can inform parents of the value of unstructured play and the advantages of play to tackle childhood obesity (Milteer et al., 2012; Whitaker, 2011). Changes in the environment and policies aimed at young children can help prevent childhood obesity. Due to the rise of childhood obesity there is a need for programs such as early detection, surveillance, and targeted

interventions that place an emphasis on preventing severe obesity in the United States (Wang, Gortmaker, & Taveras, 2011).

Useful preventive programs are mandatory to reduce childhood obesity. School programs can encourage healthy eating, provide healthy lunches, and encourage participation in physical activities. Family-based programs allows parents and siblings to assist with changing child's behavior to make healthy food selections and promote physical activities (Karnick & Kanekar, 2012). Community programs can be used to support healthy nutrition and healthy behavior through social events. Also, state or federal agencies can help with childhood obesity having food vendors provide menus with calories and limit advertisements of unhealthy foods. The government with the assistance of other health organizations are creating healthy environments which consists of access to fresh foods, bike paths, and walk paths, and playgrounds in poor neighborhoods (Karnick & Kanekar, 2012). Developing prevention programs and working together in the community are essential to combating childhood obesity,

Conclusion

In the United States childhood obesity is a major issue. The South encountered higher rates of childhood obesity compared to other regions, particularly in Georgia (Healthcare of Georgia, n.d.). Thus, the aim of this study was to explore selected variables that are linked to childhood obesity in Florida and Georgia. Factors associated to increased rates of overweight and obesity among children are complex. These elements consist of built environment, physical activity, family health and activities, and sociodemographic (Healthcare of Georgia, n.d.). The rate of childhood obesity effects

racial/ethnic minorities and children living in poorer income households. This study supports the need to address geographical disparities in the South (Meyers et al., 2015). About 35% of children ages 10 to 17 years old in Georgia and 27.5% in Florida are overweight/obese (DRC, 2012). It is imperative that people understand that social changes are necessary to reverse childhood obesity (Whitaker, 2011). Schools and communities play a crucial role in preventing childhood obesity. Policy and environmental changes can help with increasing health eating habits and physical activities among children (Philanthropic Collaborative for a Healthy Georgia, 2011). The solution for preventing childhood obesity will not be resolved quickly, therefore, tackling this problem entails a long-term obligation and investments that include widespread systematic changes within communities (Healthcare of Georgia, n.d.).

References

- Arteaga, S. S., Loria, C. M., Crawford, P. B., Fawcett, S. B., Fishbein, H. A., Gregoriou, M., ... Strauss, W. J. (2015). The healthy communities Study: Its rationale, aims, and approach. *American Journal of Preventive Medicine*, 49(4), 615-623.
doi:10.1016/j.amepre.2015.06.029
- Atkin, A. J., Corder, K., Goodyer, I., Bamber, D., Ekelund, U., Brage, S., ... van Sluijs, E. M. (2015). Perceived family functioning and friendship quality: Cross-sectional associations with physical activity and sedentary behaviours. *International Journal of Behavioral Nutrition and Physical Activity*, 12(23), 1-9.
doi:10.1186/s12966-015-0180-x
- Association of Maternal & Child Health Programs. (2014). Life course indicator: Obesity. Retrieved from http://www.amchp.org/programsandtopics/data-assessment/LifeCourseIndicatorDocuments/LC-32AB_Obesity_Final-6-16-2014_rev.pdf
- Berlin L, Norris K, Kolodinsky J, & Nelson A. (2013). The role of social cognitive theory in farm-to-school-related activities: Implications for child nutrition. *Journal of School Health*, 83, 589-595. doi: 10.1111/josh.12069
- Bethell, C., Simpson, L., Stumbo, S., Carle, A. C., Gombojav, N. (2010). National, state, and local disparities in childhood obesity. *Health Affairs*, 29(3), 347-356.
doi:10.1377/hlthaff.2009.0762
- Blumberg, S. J., Foster, E. B., & Frasier, A. M. (2012). Design and operation of the National Survey of Children's Health, 2007. National Center for Health

Statistics. *Vital Health Stat*, 1(55). Retrieved from

http://www.cdc.gov/nchs/data/series/sr_01/sr01_055.pdf

Borrell, L. N., Graham, L., & Joseph, S. P. (2016). Associations of neighborhood safety and neighborhood support with overweight and obesity in US children and adolescents. *Ethnicity & Disease*, 26(4), 469–476. doi.org/10.18865/ed.26.4.469

Carey, F. R., Singh, G. K., Brown III, H. S., & Wilkinson, A. V. (2015). Educational outcomes associated with childhood obesity in the United States: Cross-sectional results from the 2011-2012 National Survey of Children's Health. *International Journal of Behavioral Nutrition and Physical Activity*, 12(Suppl1), 1-11. doi: 10.1186/1479-5868-12-S1-S3

Carson, V., Pickett, W., & Janssen, I. (2011). Screen time and risk behaviors in 10-16-year old Canadian youth. *Preventive Medicine*, 52, 99-103. doi:10.1016/j.ypmed.2010.07.005

Centers for Disease Control and Prevention. (2012a). Florida state nutrition, physical activity, and obesity profile. Retrieved from <http://www.cdc.gov/obesity/stateprograms/fundedstates/pdf/Florida-State-Profile.pdf>

Centers for Disease Control and Prevention. (2012b). Georgia state nutrition, physical activity, and obesity Profile. Retrieved from <http://www.cdc.gov/obesity/stateprograms/fundedstates/pdf/Georgia-State-Profile.pdf>

Centers for Disease Control and Prevention. (2015a). Prevalence of childhood obesity in the United States, 2011-2012. Retrieved from

<http://www.cdc.gov/obesity/data/childhood.html>

Centers for Disease Control and Prevention. (2015b). Defining childhood obesity.

Retrieved from <http://www.cdc.gov/obesity/childhood/defining.html>

Centers for Disease Control and Prevention. (2015c). How much physical activity do children need? Retrieved from

<http://www.cdc.gov/physicalactivity/basics/children/index.htm>

Centers for Disease Control and Prevention. (2015d). NCHS data access and resources.

Retrieved from

http://www.cdc.gov/nchs/data/factsheets/factsheet_data_access_and_resources.htm

Centers for Disease Control and Prevention, National Center for Health Statistics, State and Local Area Integrated Telephone Survey. (2013). Frequently asked questions 2011-2012 National Survey of Children's Health. Retrieved from

ftp://ftp.cdc.gov/pub/Health_Statistics/NCHS/slait/nsch_2011_2012/01_Frequently_asked_questions/NSCH_2011_2012_FAQs.pdf

Center for the Study of Social Policy. (2011). Preventing childhood obesity. Retrieved

from <http://www.cssp.org/policy/papers/Preventing-Childhood-Obesity.pdf>

Cottrell, L., Zatezalo, J., Bonasso, A., Lattin, J., Shawley, S., Murphy, E., Neal, W.

- A. (2015). The relationship between children's physical activity and family income in rural settings: A cross-sectional study. *Preventive Medicine Reports*, 2, 99-104. doi: 10.1016/j.pmedr.2015.01.008
- Crespi, C. M., Wang, M. C., Seto, E., Mare, R., & Gee, G. (2015). Associations of family and neighborhood socioeconomic characteristics with longitudinal adiposity patterns in a biracial cohort of adolescent girls. *Biodemography and Social Biology*, 61(1), 81-97. doi:10.1080/19485565.2014.981794
- Creswell, J. (2009). *Research design: Qualitative, quantitative, and mixed methods approaches*. (Laureate Education, custom ed.). Thousand Oaks, CA: Sage Publications.
- Data Resource Center for Child & Adolescent Health. (n.d.a.). 2011/12 NSCH Sampling & Administration Process. Retrieved from <http://childhealthdata.org/docs/drc/2011-12-nsch-sampling-and-administration.pdf?sfvrsn=1>
- Data Resource Center for Child & Adolescent Health. (n.d.b.). Frequently asked questions about the NSCH. Retrieved from <http://childhealthdata.org/learn/NSCH/FAQ#Com1>
- Data Resource Center for Child & Adolescent Health. (n.d.c.). National Survey of Children's Health. Retrieved from <http://www.childhealthdata.org/learn/NSCH>
- Data Resource Center for Child & Adolescent Health. (n.d.d.). Guide to topics & questions asked. Retrieved from http://childhealthdata.org/learn/NSCH/topics_questions/2011-12-nsch

- Data Resource Center for Child & Adolescent Health. (n.d.e.). Compare data across state maps. Retrieved from <http://childhealthdata.org/browse/rankings/maps?s=84>
- Data Resource Center for Child & Adolescent Health. (n.d.f.). Browse by survey & topic. Retrieved from <http://childhealthdata.org/browse/survey>
- Data Resource Center for Child & Adolescent Health. (2011). Child health and health care quality measures from the NSCH and NS-CSHCN endorsed for use by the National Quality Forum. Retrieved from <http://childhealthdata.org/search-results/>
- Data Resource Center for Child & Adolescent Health. (2012). Browse the data. Retrieved from <http://childhealthdata.org/browse/rankings/maps?s=84>
- Data Resource Center for Child & Adolescent Health. (2013a). National Survey of Children's Health (NSCH), 2011/12 fast facts about the survey. Retrieved from <http://childhealthdata.org/docs/drc/2011-12-fast-facts.pdf>
- Data Resource Center for Child & Adolescent Health. (2013b). 2011/12 National Survey of Children's Health (2011/12 NSCH), sampling and survey administration. Retrieved from <http://childhealthdata.org/docs/drc/2011-12-nsch-sampling-and-administration.pdf?sfvrsn=1>
- Datar, A., Nicosia, N., & Shier, V. (2013). Parent perceptions of neighborhood safety and children's physical activity, sedentary behavior, and obesity: Evidence from a national longitudinal study. *American Journal of Epidemiology*, 177(10), 1065-1073. doi:10.1093/aje/kws353
- Dixon, B., Pena, M-M., & Taveras, E. M. (2012). Lifecourse approach to racial/ethnic

disparities in childhood obesity. *Advanced Nutrition*, 3, 73-82. doi:

10.3945/an.111.000919

Duke, N. N., Borowsky, I. W., & Petingell, S. L. (2012). Parent perceptions of neighborhood: Relationships with US youth physical activity and weight status. *Maternal and Child Health Journal*, 16, 149-157. doi:10.1007/s10995-010-0731-3

Elbel, B., Corcoran, S. P., & Schwartz, A. E. (2016). Neighborhoods, schools, and obesity: The potential for place-based approaches to reduce childhood obesity. *PLoS ONE*, 11(6), 1-12. doi:10.1371/journal.pone.0157479

Fan, Y., & Chen, Q. (2012). Family functioning as a mediator between neighborhood conditions and children's health: Evidence from a national survey in the United States. *Social Science & Medicine*, 74, 1939-1947.

Fan, M., & Jin, Y. (2013). Do neighborhood parks and playgrounds reduce childhood obesity? *American Journal of Agricultural Economics*, 96(1), 1-17. doi:10.1093/ajae/aat047

Fink, A. (2010). *Conducting research literature reviews: From the Internet to paper* (Laureate Education, Inc., custom ed.). Thousand Oaks, CA: Sage Publications.

Fisher-Owens, S. A., Soobader, M. J., Gansky, S. A., Isong, I. A., Weintraub, J. A.,...Newacheck, P. W. (2016). Geography matters: State-level variation in children's oral health care access and oral health status. *Public Health*, 134(2016), 54-63. doi: 10.1016/j.puhe.2015.04.024

- Ford, M. C., Gordon, N. P., Howell, A., Green, C. E., Greenspan, L. C., Chandra, M., ...
Lo, J. C. (2016). Obesity severity, dietary behaviors, and lifestyle risks vary by
race/ethnicity and age in a Northern California cohort of children with obesity.
Journal of Obesity, 2016, 1-10. Retrieved from
<http://doi.org/10.1155/2016/4287976>
- Frane, A. V. (2015). Planned hypothesis tests are not necessarily exempt from
multiplicity adjustment. *Journal of Research Practice*, 11(1). Retrieved from
<http://jrp.icaap.org/index.php/jrp/article/view/514/417>
- Frederick, C. B., Snellman, K., & Putnam, R. D. (2014). Increasing socioeconomic
disparities in adolescent obesity. *Proceedings of the National Academy of
Sciences of the United States of America*, 111(4), 1338-1342. Retrieved from
<http://www.ncbi.nlm.nih.gov/pmc/articles/PMC3910644/>
- Glanz, K., Rimer, B. K., & Viswanath, K. (Eds.). (2015). *Health behavior and health
education: Theory, research, and practice* (5th ed.). San Francisco, CA: Jossey-
Bass.
- Green, S. B., & Salkind, N. J. (2014). *Using SPSS for Windows and Macintosh* (7th ed.).
Upper Saddle River, NJ: Pearson.
- Guinhouya, B. C. (2012). Physical activity in the prevention of childhood obesity.
Paediatric and Perinatal Epidemiology, 26, 438-447. doi:10.1111/j.1365-
3016.2012.01269.x
- Hawkins, S. S., Gillman, M. W., Rifas-Shiman, S. L., Kleinman, K. P., Mariotti, M., &
Taveras, E. M. (2016). The linked century study: Linking three decades of clinical

and public health data to examine disparities in childhood obesity. *BioMed Central*, 16(32). doi:10.1186/s12887-016-0567-0

Healthcare of Georgia. (n.d.). Childhood obesity prevention program. Retrieved from <http://www.healthcaregeorgia.org/focus-areas/child-obesity.cfm>

Heinrich-Heine-Universität Düsseldorf. (2016). G*Power: Statistical power analyses for Windows and Mac. Retrieved from <http://www.gpower.hhu.de/>

Holt, N., Schetzina, K. E., Dalton, W. T., Tudiver, F., Fulton-Robinson, H., & Wu, T. (2011). Primary care practice addressing child overweight and obesity: A survey of primary care physicians at four clinics in Southern Appalachia. *Southern Medical Journal*, 104(1), 14–19. doi:10.1097/SMJ.0b013e3181fc968a

Institute for Work & Health. (2015). What researchers mean by...cross-sectional vs. longitudinal studies? Retrieved from <https://www.iwh.on.ca/wrmb/cross-sectional-vs-longitudinal-studies>

Kachi, Y., Otsuka, T., & Kawada, T. (2015). Socioeconomic status and overweight: A population-based cross-sectional study of Japanese children and adolescents. *Journal of Epidemiology*, 25(7), 463-469. doi:10.2188/jea.JE20140108

Kahan, D., & McKenzie, T. L. (2015). The potential and reality of physical education in controlling overweight and obesity. *American Journal of Public Health*, 105(4), 653-659. doi:10.2105/AJPH.2014.302355

Kirby, J. B., Liang, L., Chen, H-J., & Wang, Y. (2012). Race, place, and obesity: The complex relationships among community racial/ethnic composition, individual

race/ethnicity, and obesity in the United States. *American Journal of Public Health*, 102(8), 1572-1578. doi:10.2105/AJPH.2011.300452

Krueger, P. M., Jutte, D. P., Franzini, L., Elo, I., & Hayward, M. D. (2015). Family structure and multiple domains of child well-being in the United States: A cross-sectional study. *Population Health Metrics*, 13(6). doi:10.1186/s12963-015-0038-0

Letsmove.gov. (n.d.). Learn the facts. Retrieved from <http://www.letsmove.gov/learn-facts/epidemic-childhood-obesity>

Lytle, L. A. (2012). Dealing with the childhood obesity epidemic: A public health approach. *Abdom Imaging*, 37, 719-724. doi:10.1007/s00261-012-9861-y

Maher, C., Olds, T. S., Eisenmann, J. C., & Dollman, J. (2012). Screen time is more strongly associated than physical activity with overweight and obesity in 9-to-16 year-old Australians. *Acta Paediatrica*, 101, 1170-1174. doi:10.1111/j.1651-2227.2012.02804.x

Martinson, M. L., McLanahan, S., & Brooks-Gunn, J. (2012). Race/Ethnic and nativity disparities in child overweight in the United States and England. *The Annals of the American Academy of Political and Social Science*, 643(1), 219–238. doi:10.1177/0002716212445750

McCabe, B. E., Plotnikoff, R. C., Dewar, D. L., Collins, C. E., & Lubans, D. R. (2015). Social cognitive mediators of dietary behavior change in adolescent girls. *American Journal of Health Behavior*, 39(1), 51-61. doi:10.5993/AJHB.39.1.6

- Melkevik, O., Haug, E., Rasmussen, M., Fismen, A. S., Wold, B., Borraccino, A., ...
Samdal, O. (2015). Are associations between electronic media use and BMI
different across levels of physical activity? *BMC Public Health, 15*, 497.
Retrieved from <http://doi.org/10.1186/s12889-015-1810-6>
- Mertler, C. A., & Vannatta, R. A. (2013). *Advanced and multivariate statistical methods:
Practical application and interpretation*. (5th ed). Glendale, CA: Pyrczak
Publishing.
- Milteer, R. M., Ginsburg, K. R., Council on communications and media, Committee on
psychosocial aspects of child and family health, & Mulligan, D. A. (2012). The
importance of play in promoting healthy child development in poverty.
Pediatrics, 129(1), e204-213. doi:1542/peds.2011-2953
- Miyazaki, Y., & Stack, M. (2015). Examining individual and school characteristics
associated with child obesity using a multilevel growth model. *Social Science &
Medicine, 128*, 57-66.
- Myers, C. A., Slack, T., Martin, C. K., Broyles, S. T., & Heymsfield, S. B. (2015).
Regional disparities in obesity prevalence in the United States: A spatial regime
analysis. *Obesity, 23*, 481-487. doi:10.1002/oby.20963
- National Institutes of Health. (2012). Overweight and obesity statistics. Retrieved from
[https://www.niddk.nih.gov/health-information/health-statistics/overweight-
obesity](https://www.niddk.nih.gov/health-information/health-statistics/overweight-obesity)
- National Institute for Children's Health Quality. (n.d.). How much do you know about
the childhood obesity epidemic in Florida? Retrieved from

http://www.childhealthdata.org/docs/nsch-docs/florida04_23_508-pdf.pdf

- Nayak, B. K. (2010). Understanding the relevance of sample size calculation. *Indian Journal of Ophthalmology*, 58(6), 469–470. doi:10.4103/0301-4738.71673
- Nyberg, G., Sundblom, E., Norman, A., & Elinder, L. S. (2011). A healthy school start-parental support to promote healthy dietary habits and physical activity in children: Design and evaluation of a cluster-randomised intervention. *BioMed Central Public Health*, 11(1), 185-191. doi:10.1186/1471-2458-11-185
- Parikka, S., Mäki, P., Levälähti, E., Lehtinen-Jacks, S., Martelin, T., & Laatikainen, T. (2015). Associations between parental BMI, socioeconomic factors, family structure and overweight in Finnish children: A path model approach. *BioMed Central*, 15(271). doi:10.1186/s12889-015-1548-1
- Philanthropic Collaborative for a Healthy Georgia. (2011). Healthy schools, healthy communities: A guide for preventing childhood obesity in Georgia. Retrieved from <http://ghpc.gsu.edu/files/2016/07/HealthySchoolsHealthyCommunities.pdf>
- Prentice-Dunn, H., & Prentice-Dunn, S. (2012). Physical activity, sedentary behavior, and childhood obesity: A review of cross-sectional studies. *Psychology, Health, & Medicine*, 17(3), 255-273. doi:10.1080/13548506.2011.608806
- Rahman, T., Cushing, R. A., & Jackson, R. J. (2011). Contributions of built environment to childhood obesity. *Mount Sinai School of Medicine*, 78, 49-57. doi:10.1002/msj.20235

- Riis, J., Grason, H., Strobino, D., Ahmed, S., & Minkovitz, C. (2012). State school policies and youth obesity. *Maternal Child Health Journal, 16*, S111-S118. doi:10.1007/s10995-012-1000-4
- Ryabov, I. (2015). The role of residential segregation in explaining racial gaps in childhood and adolescent obesity. *Youth & Society, 1-21*. doi: 0.1177/0044118X15607165
- Sen, B., & Patel-Dovlatabadi, P. (2012). Racial disparities in obesity for males and females in three southern states in the US, across SES categories. *Health, 4*(12A), 1434-1441. doi: 10.4236/health.2012.412A207
- Seo, D.C., & Lee, C.G. (2012). Association of school nutrition policy and parental control with childhood overweight. *Journal of School Health, 82*(6), 285-293. doi: 10.1111/j.1746-1561.2012.00699.x
- Sharma, M., & Romas, J. A. (2012). *Theoretical Foundations of Health Education and Health Promotion*. (2nd ed.). Sudbury, MA: Jones & Bartlett Learning.
- Sharma, M., Wagner, D. I., & Wilkerson, J. (2006). Predicting childhood obesity prevention behaviors using Social Cognitive Theory. *International Quarterly of Community Health Education, 24*(3), 191-203. Retrieved from <http://search.proquest.com/docview/195817834?accountid=14872>
- Singh, G. K., Kogan, M. D., & van Dyck, P. C. (2010). Changes in state-specific childhood obesity and overweight prevalence in the United States from 2003 to 2007. *Archives of Pediatric & Adolescent Medicine, 164*(7), 598-607. doi:10.1001/archpediatrics.2010.84

- Sisson, S. B., Broyles, S. T., Newton, R. L., Baker, B. L., & Chernausk, S. D. (2011). TVs in the bedrooms of children: Does it impact health and behavior? *Preventive Medicine, 52*(2011), 104-108. doi:10.1016/j.ypmed.2010.11.019
- Slopen, N., Shonkoff, J. P., Albert, M. A., Yoshikawa, H., Jacobs, A.,... Williams, D. R. (2016). Racial disparities in child adversity in the U.S. *American Journal of Preventive Medicine, 50*(1), 47-56. doi:10.1016/j.amepre.2015.06.013
- Tandon, P. S., Zhou, C., Sallis, J. F., Cain, K. L., Frank, L. D., & Saelens, B. F. (2012). Home environment relationships with children's physical activity, sedentary time, and screen time by socioeconomic status. *International Journal of Behavioral Nutrition and Physical Activity, 9*(88), 1-9. Retrieved from <http://www.ijbnpa.org/content/9/1/88>
- Taylor, W. C., Upchurch, S. L., Brosnan, C. A., Selwyn, B. J., Nguyen, T. Q., ... Meininger, J. C. (2014). Features of the built environment related to physical activity friendliness and children's obesity and other risk factors. *Public Health Nursing, 31*(6), 545-555. doi:10.1111/phn.12144
- Thompson, A. E. (2015). Childhood obesity. *Journal of the American Medical Association, 314*(8), 850-850. doi:10.1001/jama.2015.6674
- Trochim, W. M. K. (2006). External validity. Retrieved from <http://www.socialresearchmethods.net/kb/external.php>
- Trust for America's Health. (2014). The state of obesity: Better policies for a healthier America 2014. Retrieved from <http://healthyamericans.org/assets/files/TFAH-2014-ObesityReport%20FINAL.pdf>

- University of Georgia. (n.d.). Obesity facts. Retrieved from
<http://obesity.ovpr.uga.edu/obesity-facts/>
- University of Michigan. (2010). Cross-sectional study/prevalence study. Retrieved from
https://practice.sph.umich.edu/micphp/epicentral/cross_sectional.php
- van Vliet, J. S., Gustafsson, P. A., Duchon, K., & Nelson, N. (2015). Social inequality and age-specific gender differences in overweight and perception of overweight among Swedish children and adolescents: A cross-sectional study. *BMC Public Health, 15*(1), 1-10. doi:10.1186/s12889-015-1985-x
- Wang, Y. C., Gortmaker, S. L., & Taveras, E. M. (2011). Trends and racial/ethnic disparities in severe obesity among US children and adolescents, 1976-2006. *International Journal of Pediatric Obesity, 6*, 12-20. doi:
10.3109/17477161003587774
- Wang, Y., & Lim, H. (2012). The global childhood obesity epidemic and the association between socio-economic status and childhood obesity. *International Review of Psychiatry, 24*(3), 176-188. doi:10.3109/09540261.2012.688195
- Wethington, H., Pan, L., & Sherry, B. (2013). The association of screen time, television in the bedroom, and obesity among school-aged youth: 2007 National Survey of Children's Health. *Journal of School Health, 83*(8), 573-581.
doi:10.1111/josh.12067
- Whitaker, R. C. (2011). The childhood obesity epidemic: Lessons for preventing socially

determined health conditions. *Archives of Pediatrics & Adolescent Medicine*, 165(11), 973–975. Retrieved from

<http://www.ncbi.nlm.nih.gov/pmc/articles/PMC3218556/>

Zilanawala, A., Davis-Kean, P., Nazroo, J., Sacker, A., Simonton, S., & Kelly, Y. (2015).

Race/ethnic disparities in early childhood BMI, obesity and overweight in the United Kingdom and United States. *International Journal of Obesity*, 39, 520-529. doi: 10.1038/ijo/2014.171