EXPLORING FAMILY MEALS, SLEEP, AND MEDIA USE AS PREDICTORS OF CHILDHOOD OVERWEIGHT/OBESE STATUS IN OKLAHOMA:

A STUDY FROM THE 2016 NATIONAL SURVEY OF

CHILDREN'S HEALTH

A DISSERTATION

SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIRMENTS

FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

IN THE GRADUATE SCHOOL OF THE

TEXAS WOMAN'S UNIVERSITY

DEPARTMENT OF HEALTH STUDIES

SCHOOL OF HEALTH PROMOTION AND KINESIOLOGY

BY

AHONDJU UMADJELA HOLMES, B.S., M.S.

DENTON, TEXAS

AUGUST 2020

DEDICATION

In memory of my beloved parents, papa Nicolas Umadjela Luyambe and maman Agnès Anekomba Umadjela, for their unfailing love and support. I wish they were here to see me at the end of this project.

For my supportive and loving husband, Carey, and our children Agnes and Abel. Thank you for hanging there with me.

For my siblings, Leopold, Marie-Jeanne, Isabelle, Astrid, Annie, Huguette, and all the clan, TrèsbondeDeboza! Thank you for cheering and encouraging me during this journey. You are a unique blessing and I thank God for each one of you.

ACKNOWLEDGEMENTS

Any dissertation requires a great deal of effort. This dissertation is not an exception. I would not have completed it without the gift of life from God. To God be the glory!

This dissertation has been written with a lot of assistance and encouragement from many people. I thank my family, my friends, and my teachers/professors for a wonderful support system during this journey. Although this page is limited to mention the details on each support, I want you to know that your help and support yielded this work.

I am grateful for the help of my dissertation committee. Dr. Mandy Golman, my committee chair, thank you for all your guidance, support, encouragement, and for patiently guiding me from the beginning. Dr. Golman, thank you for understanding what it takes to be a doctoral student and write a dissertation while being a wife, mother, and full-time employee. Your support and encouragement kept me going. To my dissertation committee members, Dr. Kristin Wiginton and Dr. Ann Amuta, thank you for your constructive feedback.

ABSTRACT

AHONDJU UMADJELA HOLMES

EXPLORING FAMILY MEALS, SLEEP, AND MEDIA USE AS PREDICTORS OF CHILDHOOD OVERWEIGHT/OBESE STATUS IN OKLAHOMA:

A STUDY FROM THE 2016 NATIONAL SURVEY OF

CHILDREN'S HEALTH

AUGUST 2020

The alarming and sustained prevalence of childhood overweight/obese status in the United States continues to generate research studies on risk factors and prevention approaches. Despite previous and current public health interventions in the US, Oklahoma ranks the sixth worst state in obesity with a third of children between 10 to 17 years being overweight or obese and one in five high school students being obese (Shape Your Future, 2018; The State of Obesity, 2019). In attempts to fill this gap and to inform future public health prevention and management strategies of childhood *overweight/obese status*, the present study examined the risk factors that significantly predict childhood *overweight/obese status* within the home environment.

Using the social cognitive theory and the social ecological model, or ecological model, as theoretical foundations, the study analyzed a representative subsample of 347 participants from the 2016 National Survey of Children's Health to determine which risk

factors (*family meals*, *sleep*, and *media use*) were the most significant at predicting *childhood overweight/obese status* in Oklahoma.

Data analysis included two phases. During the first step, univariate analysis was used to explore each variable and summarize data in a meaningful way. The second step included a bivariate analysis that examined relationships between variables and a determination of which predictor variables were associated with the dependent variable at a statistically significant level ($p < .05$) for inclusion in the logistic regression analysis. Based on this study's findings, none of the predictors of interest (family meals, sleep, and media use) was determined to be the significant risk factor in predicting childhood overweight/obese status. This study's results could indicate either that all predictors equally predict childhood overweight/obese status or that other factors related to the study design affected the results of this study. These findings differ from studies on childhood obesity and they should be carefully considered in light of similar studies.

TABLE OF CONTENTS

LIST OF TABLES

CHAPTER I

INTRODUCTION

The prevalence of children who are overweight and obese is a growing global public health concern and requires serious considerations in developed and developing countries (U.S. Department of Health and Human Services [DHHS], Centers for Disease Control and Prevention [CDC] & National Center for Health Statistics [NCHS], 2016; Harvard T.H. Chan School of Public Health [HTHC], 2018a). Moreover, numerous immediate and long-term adverse health consequences are well documented for children who are overweight and obese (Camp et al., 2017; Schuler & O'Reilly, 2017). For approximately three decades, the trends of children who are overweight and obese have gradually increased at an alarming rate in the United States before stabilizing between 2013 and 2014 (DHHS et al., 2016; HTHC, 2018a; Ogden et al., 2016).

Several studies addressing factors that increase the risk of children who are overweight and obese have identified a number of non-modifiable and modifiable factors. Some of the identified non-modifiable factors include age, sex, race/ethnicity, and parental weight status (Bagherniya, Sharma, Mostafavi, & Keshavarz, 2015; Elmore & Sharma, 2014). Modifiable factors consist of sedentary behaviors, inadequate physical activity, unhealthy eating and drinking, media screen viewing such as television, and sleep habits (Bagherniya et al., 2015; Elmore & Sharma, 2014). Though many researchers have identified factors that increase the risk of children who are overweight and obese and public health interventions are implemented to address this chronic health issue, the rapid increase of children who are overweight and obese continues to burden our society. The 2015–2016 results from the National Health and Nutrition Examination Survey (NHANES) estimated the childhood obesity rate at 18.5% among children between the ages of 2 and 19 years (CDC, 2018a). Compared to non-Hispanic Whites (14.1%) and non-Hispanic Asians (11.0%), childhood obesity prevalence is higher in Hispanics (25.8%) and non-Hispanic Blacks (22%; CDC, 2018a). Also, the prevalence of childhood obesity varies by household education and income levels. Usually, when household education and income levels increase, childhood obesity decreases, and vice versa (CDC, 2018a). According to the 2015–2016 NHANES data, the prevalence of obesity was higher (18.5%) in the lowest income group than in the highest income group (10.9%; CDC, 2018a).

The following study analyzed secondary data from the 2016 National Survey of Children's Health (NSCH) to determine which risk factors are the most significant in predicting childhood overweight/obese status. Using the social cognitive theory (SCT) and the social ecological model (SEM), or ecological model (EM), as theoretical foundations and binary logistic regression, the following study explored activities that occur in the home environment, namely family meals, sleep, and media use as predictors of overweight/obese status among children between ages 10–17 years who live in Oklahoma.

Statement of the Problem

Research shows an alarming and sustained prevalence of childhood obesity in the United States. A comparison between the national and Oklahoma obesity rate revealed that Oklahoma had a lower rate (11.8%) than the national rate (13.7%) of obesity among high school students who participated in the 2013 Youth Risk Behavior Survey (Oklahoma State Department of Health [OSDH], 2019a). While the childhood obesity rate in Oklahoma was lower than the national rate in 2013, trends continued to increase with Oklahoma's rate rising higher (17.1%) than the national rate (14.8%) in 2017 (CDC, 2018b, 2018c; OSDH, 2019b), with notable disparities by income, race, and type of insurance (CDC, 2016). Every 2 years, the CDC collects the national Youth Risk Behavior Survey, to monitor six categories of health-related behaviors that contribute to the leading causes of death and disability among high school students and adults in the US (CDC, 2018b). In addition to the Youth Risk Behavior Survey, the Fifth Grade Health Survey results indicated that the number of fifth graders who met the recommendations of at least 60 minutes of daily physical activity decreased from 2010 (33.3%) to 2014 (27%; OSDH, 2019c).

Despite previous and current public health interventions to address the prevalence of children who are overweight and obese in the US, Oklahoma ranks the sixth worst state in obesity with a third of children between 10 to 17 years being overweight or obese and 1 in 5 high school students being obese (Shape Your Future, 2018; The State of Obesity, 2019). In fact, Oklahoma ranking has changed from nineth in the 2016–2017 combined youth obesity rates to sixth in the 2017–2018 combined youth rates (The State of Obesity, 2018a, 2019). This fact is alarming given the immediate and long-term adverse health consequences, and increased medical expenditures and economic costs associated with obesity (Camp et al., 2017; Schuler & O'Reilly, 2017; Weaver, Kelley, Griggs, Weems, & Meyer, 2014). To address this epidemic at the national level, the CDC suggests better health education, more physical education and physical education programs, healthier school environments, and better nutrition services (CDC, 2017). At the state level, OSDH recommends the consumption of nutritious foods and beverages, at least 60 minutes of physical activities, less television, and 8 to 10 hours of sleep (OSDH, 2019d). While OSDH captures the implementation of these recommendations at the school level (OSDH, 2019b), data that suggests the use of these recommendations at home is not available. Moreover, research that predicts the most significant risk factors of children who are overweight and obese in Oklahoma is lacking. Identification of the risk factors that significantly predict childhood overweight/obese status within the home environment will contribute to improvements and can inform future public health interventions to address childhood overweight/obese status.

Purpose of the Study

Using secondary data from the 2016 National Survey of Children's Health, this study explored activities that occur in a home environment, namely family meals, sleep, and media use, as predictors of the overweight/obese status among children between 10–17 years old, to determine the most significant risk factors in predicting overweight/obese status in children who live in Oklahoma. This study analyzed the following variables:

- Body Mass Index-for-age-percentile, with three categories: underweight, less than the 5th percentile, Healthy, from the 5th to the 84th percentile, and Overweight or Obese, the 85th percentile and above ("Is this child currently overweight or obese, based on body mass index-for-age?;" Child and Adolescent Health Measurement Initiative [CAHMI] & Data Resource Center for Child and Adolescent Health [DRCCAH], 2018, p. 16, para. 1).
- Meals together ("During the past week, on how many days did all the family members who live in the household eat a meal together?;" CAHMI & DRCCAH, 2018, p. 169, para. 1).
- Bedtime ("How often does this child go to bed at about the same time on weeknights?;" (CAHMI & DRCCAH, 2018, p. 189, para. 1).
- Hours of sleep ("During the past week, how many hours of sleep did this child get on an average weeknight?;" CAHMI & DRCCAH, 2018, p. 190, para. 1).
- The time spent watching television/videos or playing video games ("On an average weekday, about how much time does this child usually spend in front of a TV watching TV programs, videos, or playing video games?;" CAHMI & DRCCAH, 2018, p. 170, para. 1).
- The time spent with a computer, cellphone, or electronic device ("On an average weekday, about how much time does this child usually spend with computers, cell phones, handheld video games, and other electronic devices, doing things other than schoolwork?;" CAHMI & DRCCAH, 2018, p. 171, para. 1).

- Other demographic variables:
    - Race and ethnicity of the child (“Hispanic; White, non-Hispanic; Black, non-Hispanic, Other/Multiracial, non-Hispanic;” CAHMI & DRCCAH, 2018, p. 207, para. 1).
    - Sex of the child (“Male and female children;” CAHMI & DRCCAH, 2018, p. 204, para. 1).
    - Highest education of the adults in the household (“Less than high school; High school or GED; Some college or technical school; College degree or higher;” CAHMI & DRCCAH, 2018, p. 215, para. 1)
    - Income level of the child’s household, Federal Poverty Level, FPL; “0–99% FPL; 100–199% FPL; 200–399% FPL; 400% FPL or greater;” CAHMI & DRCCAH, 2018, p. 213, para. 1)
    - The family structure of a child’s household (“Two-parent, currently married; Two parents, not currently married; Single mother; Other family types, no parent reported;” CAHMI & DRCCAH, 2018, p. 212, para. 1).

Theoretical Foundation

The present study used the social cognitive theory (SCT) and the social ecological model or ecological model (SEM/EM) as the theoretical foundation. Bandura’s SCT proposes that a person’s attributes, behaviors, and the environment continually interact in a dynamic and ongoing process (reciprocal determinism) to influence behavior (Bandura, 1986; Hammersley, Jones, & Okely, 2017; Rimer & Glanz, 2005). As one of the health behavior theories that has successfully been used in disease prevention and management, such as prevention of weight gain in children, SCT includes many constructs because it synthesizes concepts and processes from cognitive, behaviorist, and emotional models of behavior change (Hammersley et al., 2017; Rimer & Glanz, 2005).

SEM/EM is a framework that emphasizes multiple levels of influence on behavior, such as individual, intrapersonal, institutional, community, and public policy (Bronfenbrenner, 1977, 1986; Office of Disease Prevention and Health Promotion [ODPHP], 2018; Rimer & Glanz, 2005). One of the key concepts of SEM/EM, reciprocal causation, explains how people influence and are influenced by the environment in which they live (Bronfenbrenner, 1977, 1986; Rimer & Glanz, 2005). This is consistent with SCT concept of reciprocal determinism, which suggests that changes in the environment would influence behaviors such as food intake and physical activity (Bronfenbrenner, 1977, 1986; ODPHP, 2018; Rimer & Glanz, 2005). Although SEM/EM is known to influence health behaviors at multiple levels, Sallis, Owens, and Fisher (2008) noted how difficult it was to explain the interaction of different variables to affect targeted behaviors in behavior-specific interventions.

Research Questions

The study used the 2016 NSCH to answer the following research questions:

1. If childhood overweight/obese status can be predicted from the 2016 NSCH, which risk factors (family meals, sleep, and media use) are the most significant in predicting childhood overweight/obese status in Oklahoma?

2. Does the inclusion of a particular risk factor increase or decrease the probability of childhood overweight/obese status in Oklahoma?
3. Does the exclusion of a particular risk factor increase or decrease the probability of childhood overweight/obese status in Oklahoma?

Hypotheses

The study's null hypotheses were tested at the .05% significance level.

H_{01}. Family meals, sleep, and media use will be neither predictive nor protective of childhood overweight/obese status in Oklahoma.

H_{02}. Family meals, sleep, and media use will not significantly differ between children of normal weight and children who are overweight/obese in predicting childhood overweight/obese status in Oklahoma.

H_{03}. Family meals, sleep, and media use will not significantly differ by age groups (10–12 years and 13–17 years) in predicting childhood overweight/obese status in Oklahoma.

H_{04}. Family meals, sleep, and media use will not significantly differ between children who are male and children who are female in predicting childhood overweight/obese status in Oklahoma.

Delimitations

The study had the following delimitations:

- Secondary data from the 2016 NSCH representing households with non-institutionalized children between 10 to 17 years.

- Data from approximately 3,202 people who completed the 2016 NSCH survey in Oklahoma (U.S. Census Bureau, 2018).

Limitations

The limitations for this study were as follows:

1. The 2016 NSCH data were collected through online and paper survey questions, which might not be representative of all eligible people who could not participate due to lack of internet access or loss of mailed survey.
2. Data analysis was limited to a subsample of approximately 3,202 households (40.5%) out of 7,908 that completed the online or mailed survey (U.S. Census Bureau, 2018), and, as such, results are not generalizable to the general population.
3. Participants could have voluntarily or involuntarily provided misleading information while answering survey questions as a result of recall bias, lying bias, or misunderstanding of survey questions.
4. Random selection of one child per household to answer survey questions might have limited information that could have been obtained from all eligible children in each household.
5. The 2016 NSCH data collection tools have not been validated.
6. The 2016 NSCH data include only household units. This limits the scope of data that could have been collected from other types of units such as apartments, mobile homes, etc.

7. The 2016 NSCH did not use directly-measured child height and weight, but parent-reported measures to calculate body mass index-for-age percentile for children 10–17 years.

Assumptions

The assumptions for this study are as follows:

1. All survey participants understood and answered survey questions honestly.
2. All survey participants lived in households with children between the ages of 0 to 17 years at the time of the interview.
3. All survey participants completed the survey only once.

Definition of Terms

(1) **Overweight/Obese Status** – Body mass index -for-age percentile equal to the 85th percentile and above, based on the CDC's body mass index-for-age percentile. A body mass index-for-age percentile equal to the 85th and less than 95th percentile indicates an overweight status (CDC, 2015). A body mass index -for-age percentile equal to or above 95th percentile indicates an obese status (CDC, 2015). According to CAHMI and DRCCAH (2018), body mass index values were not verified because they were calculated based on parents' reports about their children's current weight and height during the time of the interview.

(2) **Sleep** – "the average number of hours and how often a child got an adequate amount of sleep based on a child's age" (CAHMI & DRCCAH, 2018, pp. 189, 190, para 1).

(3) **Family Meals** – "the number of days all family members who live in the same household ate a meal together" (CAHMI & DRCCAH, 2018, p. 169, para. 1).

(4) **Media Use** – “the average number of hours spent watching television, videos, or playing video games on a weekly basis” (CAHMI & DRCCAH, 2018, p. 170, para. 1) and “the average number of hours spent with computers, cellphones, and handheld video games on a weekly basis” (CAHMI & DRCCAH, 2018, p. 171, para. 1).

Importance of Study

Although programs that focus on preventing and managing childhood overweight/obese status have been in place for some time and continue to be implemented, the prevalence of children who are overweight and obese continues to increase. Furthermore, the immediate and long-term health consequences of this chronic health condition, especially among children with low socioeconomic status (SES) and racial/ethnic minorities, continue to be a serious public health issue. An understanding of factors that significantly predict childhood overweight/obese status could guide prevention programs within the home environment and help in their targeted implementation where they are the most needed. Prevention programs that use evidence-based approaches for their program implementation will contribute to reducing the widening health disparity gap in at-risk populations.

The study used both SCT and SEM/EM as theoretical models to predict factors within the home environment that most significantly predict childhood overweight/obese status in Oklahoma. Also, the study serves as explanatory and predictive purpose to obtain evidence that will guide childhood overweight/obese status prevention strategies within the home environment.

CHAPTER II

REVIEW OF LITERATURE

The rapid increase in the prevalence of children who are overweight/obese remains alarming. Risk factors for childhood obesity vary, are multifactorial, and no single solution exists for preventing or managing the risk factors, making it a challenging issue to change (Olson, Aldrich, Callahan, Matthews, & Gance-Cleveland, 2015; Pratt et al., 2017). Also, research consistently shows that many risk factors interact to influence childhood obesity (Grossman et al., 2017; Hoyt et al., 2014; Hulst et al., 2015). Thus, identification of the most predictable factors that predict childhood overweight/obese status in children may help develop appropriate prevention strategies that target risk factors within the home environment, especially for children who are at risk of becoming overweight/obese. The following review includes an overview of the literature related to the research questions: (1) If childhood overweight/obese status can be predicted from the 2016 NSCH, which risk factors (family meals, sleep, and media use are the most significant at predicting childhood overweight/obese status in Oklahoma? (2) Does the inclusion of a particular risk factor increase or decrease the probability of childhood overweight/obese status in Oklahoma? (3) Does the exclusion of a particular risk factor increase or decrease the probability of childhood overweight/obese status in Oklahoma?

Information Source and Search Strategy

To complete a comprehensive literature review, a search was conducted using PubMed, CINAHL, SocINDEX, PsycINFO, Child Development and Adolescent Studies, Family and Society Studies Worldwide, and Academic Search Complete. The search of key terms in combination with the Boolean logic terms “AND” and “OR” included childhood obesity, overweight, prevention and control, risk factors, family, family meals, screen media use, digital media use, and sleep. The search was restricted to English language articles published from 2014 to 2019 that included particpants between the ages 6 to 18. Excluded articles included those that were written outside the US. Additional and newer articles were handsearched using the Scopus database.

Childhood Overweight/Obese Status

Obesity is a chronic condition that is characterized by excess body fat (CDC, 2016, 2018a; National Library of Medicine [NLM], n.d.a; Obesity Action Coalition [OAC], 2018). An overweight status occurs when body weight exceeds the Body Mass Index standard of 25.0 kg/m2 and is less than 29.9 kg/m2, with or without excess fat (N.L.M n.d.b). Children whose body weight exceeds the recommended criteria for age and gender for children between 2 and 12 years old and adolescents between 13 to 18 years are categorized as being overweight or obese based on their body mass index-for-age percentile (CDC, 2015; NLM, n.d.c).

Measurement of Overweight/Obese Status

Standards for obesity measurement vary by age, sex, genetics and cultural background (CDC, 2015; NLM, n.d.a). Though excess fat is one of the characteristics of childhood obesity, no consensus exists on a cut-off point to determine the amount of excess fat that can be used as an indicator of health risk during screening (Archer, Lavie, & Hill, 2018; Ortega, Sui, Lavie, & Blair, 2016). In fact, it is time-consuming and expensive to measure body fat during clinical and epidemiological studies because dosy mass index does not differentiate between the weight of muscle and bones and the weight of fat (Archer et al., 2018; Ortega et al., 2016). To address the lack of consensus in childhood obesity screening, the CDC and the American Academy of Pediatrics (AAP) recommend the use of body mass index-for-age percentile as a criterion for weight status classification in children between the ages of 2 and 19 years (CDC, 2015; The State of Obesity, 2018a). A child's weight in kilograms is divided by the square of height in meters and expressed as a percentile from a graph or a percentile calculator to find body mass index (CDC, 2015). Body mass index-for-age percentile indicates a child's body mass index by comparing it to other children of the same gender and age (CDC, 2015; National Institute of Health [NIH], 2016).

Body Mass Index-for-Age Percentile Classification

A body mass index-for-age percentile between the 85th and 95th percentiles indicates an overweight status, a body mass index-for-age percentile equal or greater than 95th percentile suggests an obese state, percentile range for normal or healthy weight is between the 5th and the 10th body mass index-for-age percentile, and a body mass index-for-age percentile below the 5th percentile indicates an underweight status (CDC, 2015; NIH, 2016). While body mass index-for-age percentile may seem appropriate for weight status classification, it should be used along with other criteria such as waist circumference and skinfold thickness during screening due to differences in gender maturation, ethnicity, and muscle mass (Archer et al., 2018; Ortega et al., 2016). Research shows that parents tend to overestimate weight and height in younger children and underestimate them during adolescence (Gordon & Mellor, 2015; Long et al., 2016; Rendall et al., 2014; Wright, Glanz, Colburn, Robson, & Saelens, 2018). To avoid overestimates in the prevalence of childhood overweight/obese status in younger children, the 2016 NSCH calculated body mass index-for-age percentile for children 10–17 years (CAHMI & DRCCAH, 2018).

Family Meals

A family is a social group that includes parents or parent substitutes and children (NLM, n.d.c.). The number of family meals eaten together refers to the number of meals eaten together on a weekly basis at home. Family meals influence current and future dietary behaviors in children. For instance, children tend to continue practicing eating behaviors acquired during childhood into adulthood (Caldwell, Terhorst, Skidmore, & Bendixen, 2018; Frederick, Snellman, & Putnam, 2014). Excessive consumption of high caloric foods is one of the key factors for weight gain. Hence, children who are exposed to nutritious meals are more likely to consider such meals as part of their normal eating patterns and to carry their food preferences into adulthood (Caldwell et al., 2018; Rogers et al., 2017). In fact, children's consistent observation of their parents/caregivers' eating patterns leads to an increase or a decrease in the acceptance of foods that parents/caregivers eat or do not eat (Caldwell et al., 2018; Rogers et al., 2017). This complex process, known as the social modeling of eating, occurs when observation of other people's food choices and intake guides another person's choices (Cruwys, Bevelander, & Hermans, 2015; McGeown & Davis, 2017).

Most studies about the association between family meals and adolescents' obesity are cross-sectional and have mixed results, with some observing a negative association and others demonstrating a lack of association (Berge et al., 2015; Berge et al., 2018). Despite mixed results, research demonstrates that having one or two family meals per week provides a protective effect during adolescence and adulthood as a result of behaviors acquired at a younger age (Berge et al., 2015; Berge et al., 2017; Berge et al., 2018; Berge et al., 2019; Brooks, 2017; Jones, 2018). In fact, families that have frequent meals with their young children help establish behaviors that tend to continue even during adolescence (Berge et al., 2015; Brooks, 2017; Jones, 2018; Loth et al., 2018).

Mechanisms that may explain the protective association between family meals and weight outcomes in young adults include higher frequency of fruits and vegetables consumption, emotional connection and support among family members, increased sense of security for younger children, opportunities for parents/caregivers to model healthy behaviors, and recognition of satiety clues during family meals (Berge et al., 2015; Brooks, 2017; Jones, 2018). In a review that summarized research studies on the association between family and shared meals frequency and dietary outcomes as well as weight status across lifespan, researchers found that family meals and shared meals were associated with better dietary intake in both children and adults (Fulkerson, Larson, Horning, & Neumark-Sztainer, 2014; Larson, Wang, Berge, Shanafelt, & Nanney, 2016). Researchers also noted the existence of barriers to eating family meals together such as work schedule conflict (Fulkerson et al., 2014; Larson et al., 2016). Low SES families tend to experience more work schedule conflict than high SES families (Fulkerson et al., 2014; Larson et al., 2016). In most low SES families, parents tend to hold multiple jobs to make ends meet (Fulkerson et al., 2014; Larson et al., 2016). This schedule increases irregularities in the frequency of family meals. Other barriers included taste preferences, lack of time for food preparation, and lack of or reduced access to nutritious foods (Fulkerson et al., 2014; Larson et al., 2016). Neighborhoods where low SES families live tend to lack healthier food and beverages options, which limits exposure and makes it challenging to incorporate healthy meals and beverages into daily diets (Frederick et al., 2014; Larson et al., 2016). Thus, such barriers may prevent implementation of programs that promote family meals without considering the differences in family dynamics. Differences in family dynamics may prevent such initiatives from successfully being implemented in low socio-economic status families.

Sleep

Sleep is a natural and reversible state of inactivity (NLM, n.d.d). During sleep, a person's sensorimotor interaction with the environment is temporarily suspended (NLM, n.d.d). Also, a person's body is recumbent and immobile (NLM, n.d.d). An association between regular sleep and better health outcomes exists, while inadequate sleep increases the risk of adverse health outcomes, one of which is childhood obesity (Gohil & Hannon, 2018; Lewin, Wolfson, Bixler, & Carskadon, 2016; Ogilvie & Patel, 2017; Paruthi et al., 2016). An adequate amount of sleep involves "the number of nights a child sleeps for the recommended duration, based on his or her age" (CAHMI & DRCCAH, 2018, pp. 189, 190, para 1). Recommendations to obtain an adequate amount of sleep vary by age. According to the National Sleep Foundation (NSF, 2018a) recommendations, school age children (6–13 years) should have 9 to 11 hours of sleep per day and teenagers (14–17 years) should have 8 to 10 hours of sleep per day. Keeping in mind the differences in individual sleep variations due to genetic, behavioral, medical and environmental factors, the American Academy of Pediatrics, the Sleep Research Society, and the American Academy of Sleep Medicine recommend a sleep duration of 9 to 12 hours per 24 hours for children 6 to 12 years, and 8 to 10 hours per 24 hours for teenagers between 13 to 18 years (Lewin et al., 2016; Paruthi et al., 2016). Those recommendations, though they slightly differ from the NSF's in terms of extending duration by age grouping, are appropriate and necessary to guide practice (Lewin et al., 2016).

Many factors affect duration and quality of sleep. The presence of and use of electronic entertainment and communication devices such as televisions, computers, tablets, video games, and cellphones during the hour before sleep, early school start times, academic workload, and caffeine consumption negatively affect the duration and quality of sleep in children (Dube, Khan, Loehr, Chu, & Veugelers, 2017; Gohil & Hannon, 2018; Reid Chassiakos, Radesky, Christakis, Moreno, & Cross, 2016). In fact, electronic devices negatively affect sleep by emitting lights and giving off alerts for incoming calls and messages (cellphones and tablets), as well as by exposing children to violent or scary content (televisions and video games), making it difficult to fall asleep (Dube et al., 2017; LeBourgeois, et al., 2017; Reid Chassiakos et al., 2016). These bright lights emitted also reduce or suppress the production of melatonin, a sleep-inducing hormone, leading to delayed onset and reduced duration of sleep (Dube et al., 2017; Reid Chassiakos et al., 2016).

Lack of or insufficient sleep has been shown to increase both adult and childhood obesity risk due to changes in hormones that regulate hunger (ghrelin) and satiety (leptin) (Hart et al., 2017; NSF, 2018b; Ogilvie & Patel, 2017). For this reason, lack of or insufficient sleep may lead to increased sedentary activities such as television viewing and changes in eating behaviors as a result of increased appetite, inability to regulate satiety through a feeling of stomach fullness, and changes in ad libitum food intake (Hart et al., 2017; Ogilvie & Patel, 2017). Hart et al. (2017) observed these findings in their experimental study of the impact of sleep on sedentary behaviors of children aged 8 to 11 years old. Hart et al. (2017) found that children reported an increase in television viewing and caloric intake when sleep was restricted. Public health interventions that focus on obesity prevention should also address sleep, a modifiable behavior (Hart et al., 2017; Ogilvie & Patel, 2017). Since parents and caregivers play critical roles in modeling healthy lifestyles, interventions that support efforts to change the environment by restricting exposure to or usage of electronic devices, by enhancing parent-child interactions, can positively affect the amount and quality of sleep (Reid Chassiakos et al., 2016).

Media Use

Since the mid-1980s, epidemiologic studies have suggested an association between the time spent viewing screen media such as television, videos, computers, or any devices with a screen and adverse health outcomes (Reid Chassiakos et al., 2016; Robinson et al., 2017; Tanskey, Goldberg, Chui, Must, & Sacheck, 2018). Increased use of screen media by children has been associated with a higher incidence of childhood obesity, depression, the risk of developing hypertension, insulin resistance, high cholesterol, high inflammation, metabolic syndrome, and a risk for adult obesity (Lee, Kubik, & Fulkerson, 2018; Reid Chassiakos et al., 2016; Robinson et al., 2017; Tanskey et al., 2018). While this might be alarming, studies also reveal that interventions that seek to reduce the time spent using screen media positively affect behaviors and weight outcomes in children (Reid Chassiaskos et al., 2016).

The mechanisms that explain the association between increased media use and weight gain include reduced time for physical activities, increased intake of energy-dense foods/beverages during media exposure, reduced intake of fruits and vegetables, and reduced sleep (Reid Chassiakos et al., 2016; Robinson et al., 2017; Tanskey et al., 2018). In addition to that, exposure to food advertisement increases the consumption of food and beverages (Lee et al., 2018; Robinson et al., 2017). Satiety cues become obscured as children become distracted while watching screen media (Lee et al., 2018; Robinson et al., 2017). Increased screen media time leads to sleep deprivation by changing the hormones ghrelin, an appetite-regulating-hormone, and leptin, a hormone that signals increases in hunger and decreases in satiety (Gohil & Hannon, 2018; Reid Chassiakos et al., 2016; Robinson et al., 2017; Tanskey et al., 2018). This change leads to increased food/beverages consumption (Gohil & Hannon, 2018; Reid Chassiakos et al., 2016; Robinson et al., 2017; Tanskey et al., 2018). While reduction in time spent viewing screen media is likely to result in a reduction in the risk of childhood obesity, research reveals that physically engaging children during time on or off media time may mediate certain health outcomes (Odgers, 2018; Reid Chassiakos et al., 2016).

Disparities exist between the time spent using screen media and annual income. Children whose families' annual income is equal or below $35,000 tend to spend about four hours a day watching television or using electronic devices for entertainment purposes (Odgers, 2018; Reid Chassiakos et al., 2016). However, those whose families' annual income is equal or more than $100,000.00 spend about three hours a day or focus more on educational content on mobile devices than children from low socioeconomic families (Odgers, 2018; Reid Chassiakos et al., 2016). This tendency is more likely driven by living conditions. In fact, low income families tend to live in resource-limited neighborhoods with high crime levels, making it difficult to find safe areas for children to be physically active (Baer, Scherer, Richmond, Fleeger, & Hassan, 2018; Curtis, Fuller-Rowell, Doan, Zgierksa, & Ryff, 2016; Frederick et al., 2014). Consequently, more time is spent in sedentary behaviors such as watching television because of fear of being a victim of crime in these high-risk neighborhoods (Baer et al., 2018; Curtis et al., 2016; Frederick et al., 2014; Odgers, 2018; Reid Chassiakos et al., 2016).

Risk Factors

Risk factors include those "personal behavior or lifestyle, environmental exposure, inborn or inherited characteristics that, based on epidemiological evidence, are known to affect preventable health outcomes" (NLM, n.d.e, para. 1). In general, the major contributors to childhood obesity include excessive food consumption and lack of physical activities (Bagherniya et al., 2015; Elmore & Sharma, 2014; Frederick et al., 2014). Modifiable and nonmodifiable factors interact to influence obesity. Modifiable factors of childhood obesity include individual, cultural, socio-economic, and environmental factors, such as sleep habits, television viewing, dietary habits, physical activity, parents having multiple jobs, parents not being available to interact with their children, lack of safe places to play outdoors, easy access to energy-dense foods, and metabolism, to name a few (Archer et al., 2018; Bassett, John, Conger, Fitzhugh, & Coe, 2015; Dinkel et al., 2017; Urlacher et al., 2019). Nonmodifiable risk factors include an individual's genetic background, sex, and basal metabolic rate (Archer et al., 2018; Bassett et al., 2015; Dinkel et al., 2017). This study focused on modifiable risk factors within the home environment. Individual causes of childhood obesity include excessive consumption of foods/beverages high in calories such as high-fat and high-sugar content, reduced physical activities and sedentary lifestyle (Frederick et al., 2014). Cultural, socioeconomic, and environmental factors may influence behaviors at the individual level (Frederick et al., 2014). Socioeconomic and environmental factors that influence childhood obesity include family characteristics and parenting styles, school policies, demographics, and parents' employment, education, and income status (Archer et al., 2018; Frederick et al., 2014).

With attention to feeding practices, parents play significant roles because they purchase food and can decide on the type and amount of food for their children (Boots, Tiggemann, Corsini, & Mattiske, 2015; Kakinami, Barnett, Séguin, & Paradis, 2015; Yavuz & Selcuk, 2018). For this reason, parenting styles, which include attitudes and characteristics of the interactions between a parent and a child, have been shown to affect children's general health outcomes (Kakinami et al., 2015; Vaughn et al., 2016; Yavuz & Selcuk, 2018). Authoritarian and authoritative parenting styles are two of the most investigated parenting styles that appear to influence food consumption (Boots et al., 2015; Kakinami et al., 2015; Vaughn et al., 2016; Yavuz & Selcuk, 2018). In the former, parents exhibit high control and low responsiveness, while in the later, parents exhibit both high control and high responsiveness (Boots et al., 2015; Kakinami et al., 2015; Vaughn et al., 2016; Yavuz & Selcuk, 2018). Both parenting styles affect children's self-regulatory skills, with authoritarian parenting style being associated with more childhood weight problems than authoritative parenting style (Boots et al., 2015; Kakinami et al., 2015; Vaughn et al., 2016; Yavuz & Selcuk, 2018). Thus, parenting style plays an important role in influencing modifiable behaviors in children.

Obesity affects all ethnicities. Furthermore, several studies have documented a higher body mass index in children who experienced early life adversity than those who did not (Curtis et al., 2016; Curtis, Fuller-Rowell, Hinnant, Kaeppler, & Doan, 2017). In fact, early life adversity has been associated with obesity in African Americans and people from low SES (Curtis et al., 2016, Curtis et al., 2017). For example, poverty, exposure to family and neighborhood violence, exposure to a parent or a caregiver dealing with mental health issues, or abuse during childhood have been shown to affect weight status in African Americans and people from low SES (Curtis et al., 2016, Curtis et al., 2017). Some studies suggest a decrease in the prevalence of obesity among adolescents from well-educated and high-income families as opposed to adolescents from less-educated and low-income families (Baer et al., 2018; Frederick et al., 2014; Nguyen, Shuval, Bertmann, & Yaroch, 2015). If the sustained prevalence of childhood overweight/obese status is not addressed, it might perpetuate the cycle of disease, increased risk of premature morbidity and mortality. Such adverse health consequences continue to negatively affect our society, especially minority groups, people from low SES and low education levels.

As noted earlier, there are modifiable and nonmodifiable risk factors of obesity. Risk factors for childhood obesity vary, are multifactorial, and no single solution exists for preventing or managing the risk factors, making it a challenging issue to change (Berge et al., 2017; Olson et al., 2015, Pratt et al., 2017). Several studies about predictors of childhood overweight/obese status have identified non-modifiable risk factors such as age, sex, race/ethnicity, and parental weight status, and modifiable factors such as sedentary behaviors, inadequate physical activity, unhealthy eating and drinking, media screen viewing such as television, and sleep habits (Bagherniya et al., 2015; Elmore & Sharma, 2014; Robinson et al., 2017). Research consistently demonstrates that factors such as:

- excessive consumption of foods that are energy-dense, inadequate sleep;
- low family income, maternal diabetes, maternal smoking, sedentary lifestyle;
- neighborhood disadvantages such as the presence of fast foods, convenience stores or absences of grocery stores, (Grossman et al., 2017; Hoyt et al., 2014; Hulst et al., 2015);
- parental obesity, more than eight hours of watching television per week at age three, excessive weight gain during the first year of life, and excessive weight gain during the first year of life (Archer et al., 2018; Bassett et al., 2015;

Dinkel et al., 2017; Zoellner et al., 2017) interact to influence childhood obesity.

Thus, an understanding of the most significant predictors of childhood overweight/obese status will help develop appropriate prevention strategies that target children who are at risk of becoming overweight/obese.

Childhood Overweight/Obese Status: Prevalence

Prevalence of childhood obesity has not remained high in all age groups. Childhood obesity rates in children between 2 and 4 years who participated in the Women Infant and Children program have slightly declined in some states and territories of the United States from 15.9% in 2010 to 14.5% in 2014 (The State of Obesity, 2018a). However, rates remained high at 18.5 % in 2016 in children between 2 and 19 years of age (CDC, 2018d; HTHC, 2018a; The State of Obesity, 2018a), and a third of children are overweight/obese (Schuler & O'Reilly, 2017). While recent stabilization of childhood obesity sounds promising and relieving to public health professionals, policymakers and the public who are engaged in preventing and reducing childhood overweight/obese status, there are remarkable socioeconomic disparities in the prevalence and decline across different subgroups (Curtis et al., 2016; Frederick et al., 2014).

Obesity affects all ethnicities. According to the High School Risk Behavior Survey for Oklahoma, the percentage of high school students who described themselves as being obese in 2015 was 17.3% for all ethnicities, compared to the national rate 14% (CDC, n.d.). Furthermore, several studies have documented a higher body mass index in children who experienced early exposure to early life contexts than those who did not

(Curtis et al., 2016; Curtis et al., 2017). In fact, early life adversity has been associated with obesity in African Americans and people from low SES (Curtis et al., 2016, Curtis et al., 2017). Examples include poverty, exposure to family and neighborhood violence, exposure to a parent or a caregiver dealing with mental health issues, or abuse during childhood (Curtis et al., 2016, Curtis et al., 2017). If not addressed, sustained prevalence in children who are overweight/obese from minority groups, low SES, and from parents or caregivers whose education is low might perpetuate the cycle of disease, and increase the risk of premature morbidity and mortality that will continue to negatively affect our society.

As observed in some other states, Oklahoma has experienced a slight decline in childhood obesity rates among Women Infant and Children participants ages 2 to 4 year (Shape Your Future, 2018). However, it is one of the states where childhood obesity rates remain historically high, with a rate of 33.8 % among children ages10 to 17 years in 2016 (Shape Your Future, 2018; The State of Obesity, 2018b). Although the 2013 national childhood obesity rates (13.7%) appear higher than those of Oklahoma (11%; OSDH, 2019a), the increase in both national and state rates remains alarming. As the prevalence of children who are overweight/obese continues to increase, so do the questions as to what risk factors significantly predict its occurrence and what will be the most effective prevention strategies that can reverse this epidemic.

History of Childhood Overweight/Obese Status in the United States

According to Von Hipel and Nahhas (2013), little is known about the history of childhood obesity before 1963, a time during which researchers started collecting information through national surveys. National surveys revealed stability in the distribution of children's body mass index from the 1960s to 1980s and an increase until the 2000s (CDC, 2018c; Von Hipel & Nahhas, 2013). Since there was no information about childhood obesity before 1963, Von Hipel and Nahhas (2013) sought to determine whether the childhood obesity epidemic was a recent phenomenon or a continuation of longstanding trends by analyzing the body mass index of children born between 1930 and 1993 who participated in the Fels Longitudinal Study (FLS) near Dayton, Ohio. Their investigation revealed that the prevalence of childhood obesity in children born between 1930 and 1970 was low and slowly increased in boys and girls born between 1970 and 1980 (Von Hipel & Nahhas, 2013; Von Hipel, Nahhas, & Czerwinski, 2015). These findings suggest that the childhood obesity epidemic was a recent phenomenon and that reversal is possible (Von Hipel & Nahhas, 2013).

In a review of *Childhood Obesity in America: Biography of an Epidemic* by Laura Dawes (2014) and *The Nature of Childhood: An Environmental History of Growing Up in America since 1865* by Pamela Riney-Kehrberg (2014), Apple (2015) noted the authors' new insights into the history of childhood obesity in America by focusing on individual and environmental changes. The image of a chubby child shifted from being healthy during the late 19th century to becoming a health concern (obesity) in the twentieth century (Apple, 2015). The review highlights how the authors attribute the increase in childhood obesity to modifiable factors such as social, cultural, economic and environmental changes, most of which result from modern industrialization thought to have affected lifestyles (Apple, 2015; Bassett et al., 2015). Coupled together, these findings and viewpoints suggest that reversal of the epidemic of childhood overweight and obesity status is possible by addressing the factors that led to its rapid increase.

Consequences of Childhood Overweight/Obese Status

Childhood obesity leads to adverse physical health, socio-emotional, psychological, academic consequences, and economic burdens (Archer et al., 2018; Bassett et al., 2015). These consequences often continue and increase the risk of decreased quality of life in adulthood as well (Curtis et al., 2016; Frederick et al., 2014). Health consequences of childhood obesity, many of which used to be prevalent in adults but have prematurely become common in children, include fatty liver disease, sleep apnea, type 2 diabetes, asthma, cardiovascular disease, hypertension, high cholesterol, gallstones, gastric reflux, skin conditions, menstrual abnormalities, impaired balance, orthopedic problems, acceleration of puberty in both girls and boys, and death (Archer et al., 2018; Bassett et al., 2015; Dinkel et al., 2017; Zoellner et al., 2017). Socio-emotional consequences of childhood obesity include negative stereotypes, discrimination, and social marginalization (Archer et al., 2018; Bassett et al., 2015). In fact, social marginalization may take the form of exclusion from social activities, such as sports activities, because obese children tend to be slower than their peers and tend to experience shortness of breath (Archer et al., 2018; Bassett et al., 2015).

Obese children are at risk of developing psychological problems, especially in girls, as a result of low self-esteem and behavioral problems (Dinkel et al., 2017; Sagar & Gupta, 2018; Zoellner et al., 2017). Obese children often experience low self-confidence, depression, and negative body image (Archer et al., 2018; Bassett et al., 2015; Dinkel et al., 2017; Zoellner et al., 2017). Such problems may lead to isolation, a limited number of friends and limited opportunities to be physically active because of sedentary behaviors (Archer et al., 2018; Kyle, Stanford, & Nadglowski, 2018). In such circumstances, sedentary behaviors serve as a protective mechanism to avoid negative comments about weight or physical appearance (Archer et al., 2018; Kyle et al., 2018). Sedentary behaviors consist of waking hour behaviors that lead to energy expenditure of less or equal to 1.5 metabolic equivalents of task (HTHC, 2018b; Herman et al., 2015). Metabolic equivalents of task is a measure of physical activity that reflects the energy spent while sitting quietly (HTHC, 2018b; Herman et al., 2015). A person whose waking hour behaviors consist of sitting for long periods of time, using motorized transportation, watching television, playing passive video games, and using electronic device such as mobile phone or computer expends less energy than someone who includes moderate or vigorous activities (HTHC, 2018b). In fact, prolonged sitting decreases energy expenditure. For these reasons, sedentary behaviors increase the risk of weight gain (Herman et al., 2015; HTHC, 2018b). Moderate activities such as brisk walking, heavy cleaning, mowing the lawn, light bicycling, or playing double tennis increase energy expenditures by 3.0–6.0 METS (HTHC, 2018b). Furthermore, vigorous activities, for example walking, hiking, shoveling, carrying heavy loads, bicycling fast, playing basketball, soccer, or singles tennis increase energy expenditure by more than 6.0 (HTHC, 2018b).

Obese children are at risk of poor performance at school because they tend to miss school due to health issues (Sahoo et al., 2015). Sahoo et al. (2015) suggested that focusing on the causes of childhood obesity may help slow down its epidemic growth because some of the causes are more significant than others, leading to the need to identify which factors significantly increase the risk more than others. Economic burdens of childhood obesity include direct and indirect medical cost for treatment or expenses due to rehabilitation (Archer et al., 2018). In Oklahoma, estimated medical expenditures of adult overweight/obese status exceeds $1.72 billion, with a national productivity cost of absenteeism ranging from $3.38 billion to $6.38 billion (Shape Your Future, 2018). Since children who are obese are more likely to maintain obesity in adulthood (Shape Your Future, 2018), a reduction in the prevalence of childhood overweight/obese status would reduce its financial and economic burden.

Obesity increases the risk of adverse health consequences and premature death in both adults and children (CDC, 2016, 2018a; OAC, 2018). The rapid increase in the number of children who are overweight and obese is one of the most serious public health issues (Bassett et al., 2015; Elmore & Sharma, 2014; HTHC, 2018a; Liu et al., 2016). Adverse consequences such as premature morbidity and mortality, the financial burden of increased treatment, limited mobility and isolation, and increased risk of obesity in adulthood are the immediate and long-term burdens that the rapid increase of children who are overweight and obese brings to the global community (Camp et al., 2017; HTHC, 2018a; Schuler & O'Reilly, 2017). For this reason, several prevention and management strategies have been developed to reduce the prevalence of children who are overweight and obese in susceptible populations (Bassett, et al., 2015; Elmore & Sharma, 2014; HTHC, 2018a; Liu et al., 2016). However, progress in reducing the number of children who are overweight and obese has been slow as evidenced by sustained increases in its prevalence, especially in minority and low SES populations (Elmore & Sharma, 2014; Liu et al., 2016).

For approximately three decades, childhood obesity trends in the United States gradually increased at an alarming rate before stabilizing between 2013 and 2014 (DHHS et al., 2016; HTHC, 2018a; Ogden et al., 2016). The NHANES indicates that there is both an alarming and sustained prevalence of childhood obesity in the United States (CDC, 2018a). Childhood obesity management and prevention strategies have been in place for years, but given their complexity, progress has been slow.

Prevention and Management

A combination of reduced consumption of high caloric foods and increased physical activity interventions are usually implemented in preventing and managing childhood overweight/obese status (Archer et al., 2018; Dabas & Seth, 2018; Frederick et al., 2014; Ross, Flynn, & Pate, 2016). Because of that, the focus of most prevention strategies has been on modifiable behaviors such as the consumption of high caloric foods and physical activities (Archer et al., 2018; Dabas & Seth, 2018; Ross et al., 2016). Even though such strategies support attempts to curb childhood overweight/obese status by targeting research-supported risk factors, evidence continues to point to an epidemic increase in childhood obesity (Archer et al., 2018; Frederick et al., 2014; Ross et al., 2016). This increase leads to more questions than straightforward answers about specific factors that increase the risk of childhood overweight/obese (Ross et al., 2016). Given these points, research about modifiable factors that are known to increase the risk of childhood overweight/obese status provides clues about risk factors that should be targeted during prevention interventions.

Research continues to demonstrate the positive influence of family-based interventions on parents/caregivers and children. This makes such interventions one of the most viable prevention strategies in childhood obesity prevention (Dinkel et al., 2017; Weaver et al., 2014; Zoellner et al., 2017). Availability and consumption of nutritious foods coupled with an environment that promotes physical activities in the immediate surroundings of children who are at risk of becoming overweight/obese contribute to effective prevention of childhood obesity. Disparities exist in accessing nutritious foods and opportunities to increase physical activity. Research shows that children from high income and more educated families have more access to nutritious foods and opportunities to increase physical activity as compared to their peers from poor and less educated families (Baer et al., 2018; Curtis et al., 2016; Frederick et al., 2014). Compared to children from educated and high-income families, children whose parents/caregivers are less educated and whose income is low are more likely to consume high caloric foods and less likely to be physically active (Baer et al., 2018; Curtis et al., 2016; Frederick et al., 2014). Furthermore, they tend to live in resource-limited neighborhoods with high crime levels, making it difficult to find safe areas to be physically active (Baer et al., 2018; Curtis et al., 2016; Frederick et al., 2014). This serious issue needs consideration from policymakers, health professionals, and communities when prevention programs are implemented in different communities, given the adverse consequences of childhood obesity. Also, childhood overweight/obese status reduces opportunities for a community to benefit from a child's contribution to a community's social, economic, and political needs in the future, as an adult because children who are obese are more likely to become obese adults (Shape Your Future, 2018).

Summary

This section reviewed childhood overweight/obese status by explaining the key terms used in the study's research questions and by highlighting childhood overweight/obese status' prevalence, measurement, history in the US, and prevention and management strategies. It also illustrated the complexity of modifiable factors that influence childhood overweight/obese status. This study focused on modifiable risk factors that are known to increase childhood overweight/obese status at the individual, behavioral and home environment levels. As a relatively recent phenomenon, it is possible to reverse the increase in the number of children who are overweight and obese.

Theoretical Models

Social Cognitive Theory

SCT was initially referred to as social learning theory (SLT) to explain the process of learning as a function imitation (Edberg, 2020; Sharma, 2017). In other words, imitation led to learning through direct observation of a behavior of interest (Edberg, 2020; Sharma, 2017). Later, Albert Bandura introduced the concept of *self-efficacy*, the confidence that a person would perform a specific behavior, and SLT became SCT (Edberg, 2020; Sharma, 2017). SCT focuses on the impact of a person's attributes, behaviors, and the environment on health behavior change (Bandura, 1986; Edberg, 2020; Rimer & Glanz, 2005; Sharma, 2017). According to Bandura (1986), and Rimer and Glanz (2005), *reciprocal determinism* is one of the key concepts of SCT , which highlights how a person can both influence and be influenced by the environment. With that in mind, interventions that target individual and the environment in which a person lives will more likely increase the potential behavior change.

In SCT, behavior change occurs as a function of individual or internal characteristics and environmental or external factors, which summarize the key constructs of SCT (Edberg, 2020). Key constructs of the SCT that represent individual/internal characteristics include self-efficacy, behavioral capability, outcome expectations, outcome expectancies, self-control, and emotional coping (Bandura, 1986; Edberg, 2020; Rimer & Glanz, 2005; Sharma, 2017). Those that represent environmental factors include vicarious learning, situation, reinforcement, and reciprocal determinism (Bandura, 1986; Edberg, 2020; Rimer & Glanz, 2005; Sharma, 2017). Self-efficacy is a person's confidence in his/her ability to perform a behavior; behavioral capability includes a person's knowledge and skills to perform a behavior; outcome expectations reflect the likelihood and value of performing the behavior; self-control or self-regulation is a person's ability to control, to set goals, and to plan a behavior (Bandura, 1986; Edberg, 2020; Rimer & Glanz, 2005; Sharma, 2017). Vicarious learning or observational learning occurs as a result of one's observation of other people's behaviors; situation or environment includes the physical or social circumstances or conditions around a person; reinforcement reflects positive or negative responses to a person's behavior, and reciprocal determinism is the influence of a person to and by the environment (Bandura, 1986; Edberg, 2020; Rimer & Glanz, 2005; Sharma, 2017).

Advantages of using SCT in youth-related food and nutrition interventions include the use of positive reinforcement and ease at which SCT key constructs relate to real life situations (Berlin, Norris, Kolodinsky, & Nelson, 2013; Greer, Davis, Sandolo, Gaudet, & Castrogivanni, 2018). Also, SCT can easily be applied in different settings and incorporates social and personal determinants in influencing behavior (Edberg, 2020; Greer et al., 2018; Sharma, 2017). For example, youth-related food and nutrition interventions include the use of positive reinforcement, which is important to young people (Berlin et al., 2013; Greer et al., 2018). Another advantage includes the ease at which SCT key constructs relate to real life situations, such as in farm-to-school programs (Berlin et al., 2013; Greer et al., 2018; Knowlden & Sharma, 2015). Disadvantages of SCT include the complexity of its constructs, which limits its practical usage (Bandura, 1986; Edberg, 2020; Rimer & Glanz, 2005; Sharma, 2017).

Applications of Social Cognitive Theory

SCT has been applied in different health-related programs aimed at increasing confidence performing a behavior, in predicting behavior, in modeling healthy behavior, etc. (Bandura, 1986; Edberg, 2020; Rimer & Glanz, 2005; Sharma, 2017). Knowlden and Conrad (2018) incorporated five constructs of SCT in a longitudinal childhood obesity prevention trial that sought to determine the efficacy of a brief, web-based, maternal-facilitated childhood obesity program for its capacity to influence behaviors two years post intervention. The five constructs included environment, emotional coping, expectations, self-control, and self-efficacy to improve four behaviors (Knowlden & Conrad, 2018). The four behaviors consisted of daily consumption of five cups of fruits and vegetables, daily 120 minutes of structured and unstructured physical activity, increase in sugar-free beverage intake, and reduced screen and sedentary time (Knowlden & Conrad, 2018). Results demonstrated that the four behaviors improved as a result of a maternal-focused approach (Knowlden & Conrad, 2018). In particular, consumption of fruits and vegetables increased, and researchers explicitly determined which construct influenced behavior by directly measuring SCT constructs (Knowlden & Conrad, 2018).

In a qualitative meta-synthesis of secondary data that analyzed family-based interventions to prevent childhood obesity, researchers identified four SCT constructs that were applied the most (Alulis & Grabowski, 2017). These included self-monitoring, stimulus control, reinforcement, and modeling (Alulis & Grabowski, 2017). Consistent with the SCT environmental concept of vicarious learning, the study found that parents' consistence in self-monitoring food, physical activity, and sedentary behaviors predicted children's successful self-monitoring (Alulis & Grabowski, 2017). Stimulus control included changes in the home environment to reduce sedentary behavior, to increase consumption of nutritious foods, to reduce emotional eating, and to learn mindful eating techniques (Alulis & Grabowski, 2017). Reinforcement in the form of stickers, verbal praises, and other prizes such as money or point systems, were also incorporated to influence the environment (Alulis & Grabowski, 2017). Finally, modeling was applied to teach parents about the impact of their behavior on their child's behavior and attitude. The study illustrated the concept of reciprocal determinism. Observation of parents' self-monitoring, and exposure to stimulus control and reinforcement interacted to determine children's desired behavior. Thus, parents, through their actions, created an environment that contributed to children's self-efficacy, behavioral capability, and outcome expectations (Alulis & Grabowksi, 2017; Bandura, 1986; Edberg, 2020; Rimer & Glanz, 2005; Sharma, 2017). Agreeing with the outcomes of this study, McGee, Richardson, Johnson, and Johnson (2017) found that personal and environmental determinants influenced children's behaviors. For example, exposure to fruits and vegetables increased consumption, and exposure to after-school activities that children enjoyed, as well as availability of parks and community centers, increased motivation to participate in physical activities in children living in the Lower Mississippi Delta (McGee et al., 2017).

Similarly, in a study that assessed the effect of Youth Fit 4 Life on elementary children who participated in an after-school care program, researchers found that changes in self-regulatory skills usage and mood and self-efficacy significantly mediated changes in body mass index (Annesi, Walsh, Greenwood, Mareno, & Unruh-Rewkowski, 2016). Youth Fit 4 Life is an evidence-based intervention that integrates SCT constructs of self-efficacy and self-control with a supportive environment to influence behavior (Annesi et al., 2016). These findings are consistent with another study that found that self-control and self-efficacy were significant predictors of four modifiable behaviors, which were limiting television viewing, performing at least 60 minutes of daily-moderately intense physical activity, increasing daily fruits and vegetables intake to five or more cups and increasing water consumption, in a childhood obesity prevention program that targeted African American children (Elmore & Sharma, 2014). Taken together, these studies indicate that individual/internal characteristics and environmental/external factors that enhance and expose children to positive health behaviors impact weight-related outcomes in children.

Social Ecological Model

Social ecological model, or ecological model, is a framework that explains how different factors at the individual, community, organizational, and societal levels intersect to influence personal choices such as food and physical activities (Bronfenbrenner, 1977, 1986; Edberg, 2020; Jernigan et al., 2018; ODPHP, 2018; Sallis, Owen, & Fischer, 2008; Sharma, 2017). The model originates from the work of Urie Bronfenbrenner (1917–2005), a development psychologist and cofounder of the Head Start program that focuses on addressing childhood poverty in the US (Bronfenbrenner, 1977, 1986; Edberg, 2020; Sallis et al., 2008; Sharma, 2017). Bronfenbrenner's work focused on the integration of child and human development through an understanding of the five SEM/EM subsystems, namely *microsystem*, *mesosystem*, *exosystem*¸ *macrosystem*, and *chronosystem* (Bronfenbrenner, 1977, 1986; Edberg, 2020; Sharma, 2017). These five systems illustrated how development and behavior could be understood as an outcome of the interaction between an individual and the different subsystems of the ecological system (Bronfenbrenner, 1977, 1986; Edberg, 2020; Sharma, 2017). Bronfenbrenner described the five subsystems as: microsystem (the relationship between a child and immediate components of his/her environment like family, school, neighborhood, and the childcare), mesosystem (the relationships between one or more settings, like home, school, community), exosystem (the relationships between different element of the system that do not directly interact with the child, like a child's home and father's job), macrosystem (a reference to culture, values, lifestyles, beliefs, etc.), and chronosystem (a representation of environmental changes over time; Bronfenbrenner, 1977, 1986; Edberg, 2020; Sharma, 2017). As the SEM/EM evolved, it developed into a complex process that represented six levels of intervention: intrapersonal or individual, interpersonal, social, cultural, organizational, and policy/environmental levels (Jernigan et al., 2018; Sallis et al., 2008; Sharma, 2017). At each level, different factors were targeted during interventions though not all at the same time.

This model can be both an advantage and disadvantage. Advantages of SEM/EM include the incorporation of different levels of influence on behaviors; it looks at a broader picture in designing intervention programs. Although SEM/EM is known to influence health behaviors at multiple levels, its complexity makes it difficult to explain the interaction of different variables in influencing behaviors (Edberg, 2020; Sallis et al., 2008). The built environment presents opportunities for physical activities through availability of safe neighborhoods, the presence of safe infrastructures for physical activity, and access to nutritious foods (Hoyt et al., 2014).

Applications of Social Ecological or Ecological Model

SEM/EM focuses on different levels of influence on behavior. As such, it has been studied and applied in different childhood obesity-related studies or interventions. For example, Jernigan et al. (2018) used levels of SEM (individual, interpersonal, institutions/organizations, community, systems/policies) to map policies and programs that reported a small childhood obesity rates decline in four different states between 2003 and 2012, and to examine across and within levels of SEM to understand their influence on implementation success at each site. Researchers found that despite the differences in childhood obesity prevention program implementation at each location, all four sites had cross-sector partnerships working together in coordinated comprehensive ways across and within SEM levels, which helped implement comprehensive approaches to address childhood obesity (Jernigan et al., 2018). The use of SCT and SEM in childhood overweight/obese status prevention offers a foundation for creating broader initiatives to reduce childhood obesity by highlighting risk factors that seem to influence children's weight status.

In their pilot study on family-based programs to address childhood obesity, Weaver et al. (2014) applied SEM theoretical framework in a family-based behavioral change program. During the intervention, Weaver et al. (2014) taught motivational interviewing strategies to physicians. At the interpersonal level, physicians used motivational interviewing strategies to engage parents and their children during family group medical visits and workshops (Weaver et al., 2014). At the community level, a collaboration with graduate students was established to plan and implement evidence-based nutrition education sessions (Weaver et al., 2014). In addition to the nutrition component, a faculty member and trained students/volunteers conducted physical activities sessions (Weaver et al., 2014). As a result of the family-based intervention at the interpersonal and community level, parents and children increased consumption of healthy foods and decreased sedentary behaviors (Weaver et al., 2014). Physicians and other professionals also benefited from this intervention. They learned about relating to patients/clients through motivational interviewing (Weaver et al., 2014). While the intervention improved participants' behaviors, Weaver et al. (2014) noted that barriers such as lack of community input and shared leadership from local stakeholders contributed to restricted recruitment, poor retention and reduced participation. This study illustrates the benefits of working with different levels of influence to affect behavior and increase participation.

Expanding on an ecological framework that emphasizes social and environmental changes at multiple levels, Wilson, Sweeney, Kitzman-Ulrich, Gause, and St. George (2017) reviewed the impact of evidence-based interventions that combined parental support, motivational and behavioral factors on weight loss of youth, especially those from underserved ethnic minority groups. Wilson et al. (2017) argued that positive parenting skills, autonomy support, and behavioral skill training influenced weight loss in children. This result is consistent with the growing number of studies that demonstrate the impact of positive environments within the context of families, schools, communities, and healthcare settings on children's health-related behaviors (Wilson et al., 2017).

Guided by previous research on ecological model and potential risk factors of childhood overweight/obese status, such as the Six-Cs ecological model (Dev, McBride, Fiese, Jones, & Cho, 2013), Fiese and Bost (2016) suggested that no single cause increases the risk of childhood overweight/obesity. Fiese and Bost (2016) focused on different regulatory processes that connect ecologies and that may affect weight status in children. These include biological, child, family systems, and food environment regulations, which interact to influence (Fiese & Bost, 2016). Despite their central role preventing childhood obesity, families are often left out in the planning phases of healthy living campaigns (Fiese & Bost, 2016). Fiese and Bost (2016) suggested the inclusion of families in the planning phases of healthy living campaigns by increasing families' partnerships with childcare settings, schools, parks, and other organizations that promote healthy lifestyles.

While the aforementioned study applied SEM/EM framework to identify factors that increased the risk of childhood overweight/obese status, another study, by Kellous, Sandalinas, Copin, and Simon (2014), tried to highlight unresolved issues of SEM/EM. In the study, researchers evaluated to what extent integration of a SEM/EM approach into physical activity and sedentary behavior interventions has impacted their success on weight status (Kellous et al., 2014). Interestingly, studies that targeted physical activity determinants at different levels of the SEM/EM, including the social and organizational/built environment, had the highest potential to prevent obesity in youth (Kellous et al., 2014). Due to the wide variety of approaches used in interventions under review, Kellous et al. (2014) and Pratt et al. (2017) did not find conclusive outcomes about the specific components of interventions that were needed to achieve beneficial effects on obesity.

Summary

SCT and SEM/EM have been extensively used in different interventions. They both suggest that behavior can be influenced by individual and environmental factors. Compared to SCT, SEM/EM is more complex because it includes six levels of influence on behavior. Despite their disadvantages, SCT and SEM/EM have been successfully used in different settings. With that in mind, it is possible to adapt SCT and SEM/EM to different settings by focusing on their usefulness in changing behavior, and by recognizing the limitations of each.

CHAPTER III

METHODOLOGY

This quantitative, ex-post facto study used population-based cross-sectional secondary data from the 2016 National Survey on Children's Health to explore family meals, sleep, and media use as predictors of overweight/obese status among children between 10–17, to determine the most significant risk factors that predict childhood overweight/obese status in children who live in Oklahoma. Between June 2016 and February 2017, the NSCH was administered by the U.S. Census Bureau, Associate Director for Demographic Programs, on behalf of the U.S. Department of Health and Human Services and the Maternal and Child Bureau (CAHMI, 2017). According to the U.S. Census Bureau (2017), the NSCH is the only national and state-level survey on the health and wellbeing of children, their families, and communities. The 2016 NSCH dataset provides a large data set with key indicators of children's health that can be utilized for the study of different aspects of children's health and wellbeing (CAHMI, 2017).

Population and Sample

The 2016 NSCH dataset represents anonymous information from 50,212 child-level questionnaires completed nationally and approximately 985 per state (CAHMI, 2017). With child-level survey, researchers randomly contacted households by mail to randomly identify one child who will participate in the survey (CAHMI, 2017).

Sampling Procedures

Researchers used an address-based sampling process to collect data through internet-based web and mailed paper data collection instruments (CAHMI, 2017; U.S. Census Bureau, 2017). To identify households with children and to improve sampling efficiency, data was collected using the Census Bureau's Center for Administrative Records Research and Applications (U.S. Census Bureau, 2017). Researchers divided the sample into two strata, households with children under 18 (Stratum 1) and households without children (Stratum 2; U.S. Census Bureau, 2017). Households with children ages 17 years old, or younger, living in the home at the time of the interview, were eligible (CAHMI, 2017). The present study included a total of 7,908 households from Oklahoma that met inclusion criteria, with 4,490 households in Stratum 1 and 3,418 households in Stratum 2, and 3,202 (40.5%) from completed mailed or online surveys (U.S. Census Bureau, 2018, p. 64). To account for nonresponses and oversampling, the 2016 NSCH used different adjusted sample weighs formulas to allow for estimates to be representative of the population (U.S. Census Bureau, 2018, p. 54).

Protection of Human Participants

Information about the 2016 NSCH participants is non-identifiable. An Institutional Review Board (IRB) exempt review application was submitted to Texas Woman University's IRB committee for review and was approved before data analysis.

Data Collection

The 2016 NSCH was collected from June 10, 2016, through February 10, 2017 (U.S. Census Bureau, 2017). To collect data for the 2016 NSCH, researchers used administrative data to identify households that would more likely include children between 0 to 17 years (CAHMI, 2017). Then, non-institutionalized civilians living in household units were randomly selected using household addresses across the United States (CAHMI, 2017). Researchers mailed instructions to access the survey online and at least one reminder letter, and a paper screening questionnaire to households that did not access the online survey (CAHMI, 2017; see Appendices B and C). To encourage participation and reduce response bias, the 2016 NSCH divided the sample into thirds and used three incentives categories ($0.00, $2.00, or $5.00) that were randomly assigned to each third of the sample (CAHMI, 2017).

Data Collection Instruments

Researchers developed the 2016 NSCH to "reduce redundancy, include relevant topics, and improve assessment methods by consolidating the previous NSCH and the National Survey of Children with Special Health Care Needs (NS-CSHCN) NSCH with special needs" (CAHMI, 2017, p. 14). The NSCH used both web (online) and paper instruments in both English and Spanish (U.S. Census Bureau, 2018). A mailed invitation was sent to selected households, inviting them to respond to the web survey (CAHMI, 2017). Once online and after reviewing the Privacy Act statement, participants had to verify their address and answered questions about eligible children residing in the home (CAHMI, 2017). Households that did not meet eligibility criteria during screening were removed from future mailings (CAHMI, 2017). Those who did not respond to the first two web surveys received a mailout/mail back self-administered paper-and-pencil interviewing screener instrument (CAHMI, 2017).

The 2016 NSCH survey instrument consisted of a pre-survey screener, which had 10 questions to identify households that had at least one eligible child, and 11 topical survey sections (CAHMI, 2017; U.S. Census Bureau, 2018). Survey sections included:

> (1) This child's health; (2) This Child as an Infant; (3) Health Care Services; (4) Experience with This Child's Health Care Providers; (5) This Child's Health Insurance Coverage; (6) Providing for This Child's Health; (7) This Child's Learning (0–5 years); (8) This Child's Schooling and Activities (6–17 years); (9) About You and This Child; (10) About Your Family and Household; (11) About You; (12) Household Information. (CAHMI, 2017; U.S. Census Bureau, 2018, p. 15).

According to CAHMI (2017), a total of 139,923 households completed the survey nationwide, with about 2,744 surveys completed per state. This study focused on children between 10–17 years because body mass index-for-age percentile are only available for this age group. The 2016 NSCH did not use directly-measured child height and weight, but parent-reported measures to calculate body mass index-for-age percentile for children 10–17 years (CAHMI & DRCCAH, 2018)

Data Analysis

Research Questions

The current study answered the following research questions:

1. If childhood overweight/obese status can be predicted from the 2016 NSCH, which risk factors (family meals, sleep, and media use) are the most significant at predicting childhood obesity in Oklahoma?

2. Does the inclusion of a particular risk factor increase or decrease the probability of childhood overweight/obese status in Oklahoma?
3. Does the exclusion of a particular risk factor increase or decrease the probability of childhood overweight/obese status in Oklahoma?

Hypotheses

H_{01}. Family meals, sleep, and media use will be neither predictive nor protective of childhood overweight/obese status in Oklahoma.

H_{02}. Family meals, sleep, and media use will not significantly differ between children of normal weight and children who are overweight/obese in predicting childhood overweight/obese status in Oklahoma.

H_{03}. Family meals, sleep, and media use will not significantly differ by age groups (10–12 years and 13–17 years) in predicting childhood overweight/obese status in Oklahoma.

H_{04}. Family meals, sleep, and media use will not significantly differ between children who are male and children who are female in predicting childhood overweight/obese status in Oklahoma.

Variables Used in the Study

Dependent variable: Overweight/obese status. The dependent variable, *overweight/obese status*, was measured using body mass index-for-age percentile, with three categories: underweight (less than the 5th percentile), healthy (5th percentile to 84th percentile), overweight or obese (85th percentile or above; “Is this child currently overweight or obese, based on body mass index-for-age?;” CAHMI & DRCCAH, 2018,

p. 16, para. 1). Prior to analyzing data in this study, body mass index-for-age percentile was recoded into two categories to include healthy weight only (0) and overweight/obese (1).

Independent variables: Family meals, sleep, and media use. ***Family meals.*** To measure family meals, the number of days all family members who live in the household eat a meal together survey variable was used. In the 2016 NSCH survey, the number of meals was measured in days, with four categories (CAHMI & DRCCAH, 2018). Family meals variable was collapsed into three categories (1 = *0 to 3 days*, 2 = *4 to 6 days*, 3 = *everyday*).

Bed time. Bed time measured how often a child goes to bed at about the same time (CAHMI & DRCCAH, 2018). Hours of sleep compared a child's hours of sleep to the recommended age-specific guidelines (CAHMI & DRCCAH, 2018). Another variable, past week sleep average (During the past week, how many hours of sleep did this child get on an average weeknight?) was also included as a measure of sleep because it contained more precise values than the variables bed time and hours of sleep (1 = *less than 6 hours*, 2 = *6 hours*, 3 = *7 hours*, 4 = *8 hours*, 5 = *9 hours*, 6 = *10 hours*, 7 = *11 or more hours*) than those for bed time and hours of sleep, past week sleep average was included in the analysis (CAHMI & DRCCAH, 2018).

Media use. To measure media use, the time spent watching television/videos or playing video games and the time spent with a computer, cellphone or electronic handheld video game, and other electronic devices, doing things other than schoolwork were used. The time spent watching television/videos or playing video games measured the daily amount of time a child spends in front of a TV watching TV programs, videos, or playing video games ("0 = *Do not watch TV*, 1 = *Watch TV less than 1 hour per day*, 2 = *Watch TV 1-3 hours per day*, 3 = *Watch TV 4 hours or more per day*;" CAHMI & DRCCAH, 2018, p. 170, para. 5). The time spent with a computer, cellphone or electronic device measured the amount of time a child spent with computers, cell phones, handheld video games, and other electronic devices, doing things other than schoolwork ("0 = *Do not use electronic devices*, 1 = *Use electronic devices less than 1 hour per day*, 2 = *Use electronic device 1-3 hours per day*, 3 = *Use electronic devices 4 hours or more per day*;" CAHMI & DRCCAH, 2018, p. 171, para. 5).

Covariates. Covariates included demographic variables race and ethnicity of child (1 = *Hispanic*; 2 = *White, non-Hispanic*; 3 = *Black, non-Hispanic;* 4 = *Other/Multiracial, non-Hispanic*; CAHMI & DRCCAH, 2018), sex of child (1 = *Male* and 2 = *female*; CAHMI & DRCCAH, 2018), highest education of adult in the household (1 = *Less than high school*, 2 = *High school or GED*, 3 = *Some college or technical school*, 4 = *College degree or higher*; CAHMI & DRCCAH, 2018), income level of child's household, recorded as a percentage Federal Poverty Level (FPL) (1 = *0–99% FPL*, 2 = *100–199% FPL*, 3 = *200–399% FPL*, 4 = *400% FPL or greater*; CAHMI & DRCCAH, 2018), age of selected child was collapsed into two groups (1 = *10–12* and 2 = *13–17*), and family structure of a child's household (1 = *Two-parent, currently married*; 2 = *Two parents, not currently married*; 3 = *Single mother*; 4 = *Other family type, no parent reported*; CAHMI & DRCCAH, 2018). Family structure of a child's household was collapsed into two categories, single-parent (0) and two-parents households (1).

Data Analysis Plan

Data analysis included two phases, using IBM SPSS statistics Version 25 (SPSS Inc., Chicago, IL). First, all data were analyzed descriptively using univariate analysis to explore each variable and summarize data in a meaningful way. During the second step, bivariate analysis was used to examine relationships between demographic variables (race/ethnicity, sex of selected child, income level of child's household, highest education of adult in household, family structure of a child's household, and age of selected child) and dependent variable (overweight/obese status), and the relationship between independent variables (family meals, sleep, and media use) and dependent variable were examined. This step also helped identify variables that were associated with the dependent variable (overweight/obese status) at a statistically significant level ($p < .05$) and use them in a binary logistic regression analysis to model the dependent variable (overweight/obese status) as a function of predictor variables (family meals, sleep, and media use).

Prior to analysis, the variable body mass index of child was recoded as a dichotomous variable and applied the following transformations: 0 = *healthy weight*, 1 = *overweight/obese*. Also, other variables were collapsed into smaller categories due to low cell values . The independent variable family meals (number of days all the family members who live in the household ate a meal together during the past week) was recoded into three categories (1 = *0 to 3 days*, 2 = *4 to 6 days*, 3 = *everyday*). Independent variable sleep (bed time) was recoded into three categories (1 = *Always/Usually*, 2 = *Sometimes*, 3 = *Rarely or Never*), sleep (past week sleep average) was recoded into two categories, based on the American Academy of Pediatrics', the Sleep Research Society's, and the American Academy of Sleep Medicine's recommendations by age group (Lewin et al., 2016; Paruthi et al., 2016), with 8 hours or more being coded as healthy (0) and 7 hours or less as unhealthy (1). Media use (the time spent watching television/videos or playing video games) was recoded into three categories (1 = *Do not watch/Watch less than 1 hour per day*, 2 = *Watch 1–3 hours per day*, 3 = *Watch 4 or more hours per day*), and media use (time spent with a computer, cellphone or electronic device) was recoded into three categories (1 = *Do not use electronic devices/Use electronic devices less than 1 hour per day*, 2 = *Use electronic device 1–3 hours per day*, 3 = *Use electronic devices 4 hours or more per day*). Descriptive variables family structure of a child's household was recoded into two categories (0 = *single parent*, 1 = *two-parents*), and highest education of adult in the household was recoded into three categories (1 = *Less than high school/High school* or GED, 2 = *Some college or technical school*, 3 = *College degree or higher*). Lastly, the the descriptive variable age of selected child was modified to include only children between the ages of 10 to 17 years, which is the age group of interest for this study.

After preparing data for analysis and screening for missing data, it was observed that out of 764 recorded cases, 60.7% (464 cases) contained missing data. Further, out of 13 variables of interest, 69.2% (9 variables) contained missing data. This amounted to a total of 8.1% missing information in the dataset. Particularly, the dependent variable overweight/obese status had the highest number of missing data (54.7%, n = 417) with less than half responses (46.5%, n = 347) to the measure of interest (overweight/obese status). Because the variable overweight/obese status was crucial to the analyses, all participants with missing information about the variable of interest were removed from the dataset. The final subsample contained participants who had answered to the measure of interest (n = 347). Removal of cases with missing values for overweight/obese status yielded 13.54% (n = 47) cases with a total of 1.3% missing information in the dataset.

CHAPTER IV

RESULTS

This chapter presents the results of the analyses that were conducted to answer the research questions and test hypotheses. It is subdivided into preliminary and primary analyses. Preliminary analyses presents descriptive analyses of all variables used in the study. Primary analyses comprise two components. First, they present bivariate analyses between demographic and dependent variables. Next, they answer research questions and test hypotheses.

Preliminary Analyses

Demographic Variables

Frequencies and percentages for the categorical demographic variables (Race/Ethnicity, Sex of Child, Highest education of Adult in the Household, Income Level of Child's Household, Family Structure of Child's Household, Age of Selected Child) are displayed in Table 1. Responses to survey questions were obtained from a sub-sample of 347 participants. Table 1 displays the missing value percent for variables with less than 10% missing values. The majority of participants were male (51.9%; n = 180) and White Non-Hispanic (57.3%; n = 199). A greater number of adults had a college or a higher education level (52.4%; n = 182), which does not include the percentage of those who did not provide their information about their education level (2.0%; n = 7). Also, more participants reported a FPL of 400% or greater (37.2%; n = 129) and a two-parent household family structure (68.9%; n = 239), which does not include the percentage of missing values (11.2%; n = 39) for family structure. Finally, more than half of children who were selected to answer interview questions were between 13 and 17 years old (69.7%; n = 242) with children who were 15 years comprising the majority of this age group (17.3%; n = 60).

Table 1

Frequencies and Percentages for Categorical Demographic Variables (n = 347)

Categorical Demographic Variable	*n*	%
Gender		
Female	167	48.1
Male	180	51.9
Race/Ethnicity		
White, Non-Hispanic	199	57.3
Black, non-Hispanic	13	3.7
Hispanic	49	14.1
Other/Multi-racial, non-Hispanic	86	24.8
Highest education among reported adults of child's household		
Less than high school/High school or GED	68	19.6
Some college or technical school	90	25.9
College degree or higher	182	52.4
Income level of a child's household (FPL)		
0–99% FPL	32	9.2
100–199% FPL	63	18.2
200–399% FPL	123	35.4
400% FPL or greater	129	37.2
Family structure of child's household		
Single parent household	69	19.9
Two parent household	239	68.9

Age of selected child		
10 to 12 years	105	30.3
13 to 17 years	242	69.7
Age of selected child in years		
10	37	10.7
11	29	8.4
12	39	11.2
13	41	11.8
14	42	12.1
15	60	17.3
16	55	15.9
17	44	12.7

Note. Frequencies not summing to *n* = 347 reflect missing data.

Independent Variables

Descriptive statistics for the predictor variables (family meals, sleep, and media use) are displayed in Table 2. The highest proportion of participants ate a meal together for 4 to 6 days during the past week (37.2%; *n* = 129 and 0.6% missing value; *n* = 2). Variables bed time, hours of sleep, and past week sleep average measured sleep. The majority of participants reported that children usually or always went to bed at the same time on weeknights (84.7%; *n* = 294 and 0.3% missing responses; *n* = 1), that they slept recommended age-appropriate hours (62.8%; *n* = 218 and 0.9% missing responses; *n* = 3), and that the majority of children slept for eight hours or more per night during the past week (72.3%; *n* = 251; and 0.9% missing responses; *n* = 3). The time spent watching television/videos or playing video games and the time spent with a computer, cellphone or electronic device measured media use. More participants reported that children spent an average of one to three hours watching television, videos or playing video games daily

(73.5%; *n* = 255 and 0.9% missing responses; *n* = 3). Also, they spent an average of one to three hours with a computer, cellphone or electronic device (65.4.0%; *n* = 227 and 0.6% missing responses; *n* = 6).

Table 2

Frequencies and Percentages for Categorical Independent Variables (n = 347)

Categorical Independent Variable	*n*	%
Family Meals		
0 to 3 days	117	33.7
4 to 6 days	129	37.2
everyday	99	28.5
Sleep: Bedtime		
Always/Usually	294	84.7
Sometimes	35	10.1
Rarely or never	17	4.9
Sleep: Hours of sleep		
Child sleeps recommended age-Appropriate Hours	218	62.8
Child sleeps less than recommended age-appropriate hours	126	36.3
Sleep: Past week sleep average		
Unhealthy (7 hours or less)	93	26.8
Healthy (8 hours or more)	251	72.3
Media Use: The Time Spent with a Computer, Cellphone or Electronic Device		
Do not watch/Watch TV less than 1 hour per day	53	15.3
Watch TV 1–3 hours per day	255	73.5
Watch TV 4 hours or more per day	36	10.4
Media Use: The Time Spent with a Computer, Cellphone or Electronic Device		
Do not use electronic devices/Use	41	11.8

electronic devices less than 1 hour		
Use electronic devices 1–3 hours per day	227	65.4
Use electronic devices 4 hours or more per Day	77	22.2

Note. Frequencies not summing to *n* = 347 reflect missing data.

Dependent Variable

Frequencies and percentages for the categorical dependent variable overweight/obese status (measured using body mass index of child, healthy weight only = 0 and overweight/obese = 1) are displayed in Table 3. As shown below, more than half of respondents indicated a healthy weight status for children (67.1%; *n* = 233) and about one third were overweight/obese (32.9%; *n* = 114).

Table 3

Frequencies and Percentages for Categorical Dependent Variable (n = 347)

Categorical Dependent Variable	*n*	%
Healthy weight only	233	67.1
Overweight or obese	114	32.9

Primary Analyses

The following section presents statistical analyses that were carried out to answer research questions and test hypotheses. At first, bivariate analyses of independent variables family meals, sleep, and media use by the dependent variable overweight/obese status, followed by the demographic variables by the dependent variables are presented.

Next, bivariate analysis of the demographic variables by the dependent variables are presented. In the final analysis, logistic regression results are presented.

Research Question 1 and Hypotheses 1–4

In this section, crosstabulations using Pearson's chi-square and Cramer's V tests were conducted to examine the relationship between the independent variables and dependent variable. Results from this analysis were used to identify independent variables that had a statistically significant relationship ($p < .05$) with the dependent variable and examine them in a logistic regression analysis.

This section answered Research Question 1:

Research Question 1. If childhood overweight/obesity status can be predicted from the 2016 NSCH, which risk factors (family meals, sleep, and media use) are the most significant at predicting childhood overweight/obese status in Oklahoma?

The following hypotheses were tested:

H_{01}. Family meals, sleep, and media use will be neither predictive nor protective of childhood overweight/obese status in Oklahoma.

H_{02}. Family meals, sleep, and media use will not significantly differ between normal weight children and children who are overweight/obese in predicting childhood overweight/obese status in Oklahoma.

H_{03}. Family meals, sleep, and media use will not significantly differ by age groups (10–12 years and 13–17 years) in predicting childhood overweight/obese status in Oklahoma.

H_{04}. Family meals, sleep, and media use will not significantly differ between children who are male and female in predicting childhood overweight/obese status in Oklahoma.

Table 4 presents a bivariate analysis of the variables family meals, sleep, and media use with the dependent variable overweight/obese status. Three survey items were used to measure the variable sleep (bed time, past week sleep average, and hours of sleep). Media use was measured using the daily average time spent watching television, videos or playing video games and the daily average use of computer, cellphone or electronic devices. Overall, the chi-square analysis indicated that the relationship between all the independent variables and dependent variable was not statistically significant (family meals p = .477; sleep - bed time p = .824; sleep - past week sleep average p = .212; sleep - hours of sleep p = .281; media use - daily average time spent watching television, videos, or playing video games p = .513, and media use - daily average use of computer, cellphone, or electronic devices p = .581).

Since the criteria for inclusion of variables in the logistic regression was set to include predictor variables that would relate to the dependent variable at a statistically significant level ($p < .05$) and that none of them met the criteria, results for the logistic regression with predictor variables (family meals, sleep, and media) were not included in this section because the model was not statistically significant, logistic regression analysis as they would be regarded as occurring by chance.

Table 4

Frequencies and Percentages for Independent Variables by Body Mass Index of Child

Variable	Healthy Weight		Overweight/Obese				Cramer's
	n	%	*n*	%	χ^2	*p*	*V*
Family meals (days)					1.48	.477	.066
0 to 3	77	33.3[a]	40	35.1[a]			
4 to 6	83	35.9[a]	46	40.4[a]			
Everyday	71	30.7[a]	28	24.6[a]			
Sleep: Bedtime					.387	.824	.033
Always/ Usually	198	85.3[a]	96	84.2[a]			
Sometimes	22	9.5[a]	13	11.4[a]			
Rarely or Never	12	5.2[a]	5	4.4[a]			
Sleep: Past week sleep average (Hours)					1.55	.212	.067
Age-Appropriate	151	65.7[a]	67	58.8[a]			
Less than age-appropriate	79	34.3[a]	47	41.2[a]			

(continued)

Frequencies and Percentages for Independent Variables by Body Mass Index of Child

Variable	Healthy Weight *n*	Healthy Weight %	Overweight/Obese *n*	Overweight/Obese %	χ^2	*p*	Cramer's *V*
Sleep: Hours of sleep					1.62	.281	.058
Healthy (8 hours or more)	172	74.8[a]	79	69.3[a]			
Unhealthy (7 hours or less)	58	25.2[a]	35	30.7[a]			
Media Use: Daily average time spent watching Television, videos or playing video games					1.34	.513	.062
Do not watch or watch < 1 hour	39	17.0[a]	14	12.3[a]			
1 – 3 hours	168	73[a]	87	76.3[a]			
4 or more hours	23	10.0[a]	13	11.4[a]			

(continued)

Frequencies and Percentages for Independent Variables by Body Mass Index of Child

Variable	Healthy Weight		Overweight/Obese				Cramer's
	n	%	*n*	%	χ^2	*p*	*V*
Media Use: Daily average use of computer, cellphone or electronic device					1.05	.581	.581
Do not use electronic devices/Use < 1 hour	27	11.7[a]	14	12.3[a]			
1 – 3 hours	156	67.5[a]	71	62.3[a]			
4 or more hours	48	20.8[a]	29	25.4[a]			

Note. For each category, pairs of column proportions with different superscripts differed significantly, $p < .05$.

Research Question 1: Demographic and Dependent Variables

While Research Question 1 sought to identify predictors (family meals, sleep, and medias use) that were the most significant at predicting childhood overweight/obese status in Oklahoma, the relationship between demographic and dependent variables was tested in this section to identify other factors that might be significant at predicting childhood overweight/obese status.

Crosstabulations using Pearson's chi-square and Cramer's V tests were conducted to examine the relationship between demographic and dependent variables, and identify demographic variables associated with the dependent variable at a statistically significant level ($p < .05$). As illustrated on Table 5, the chi-square analysis indicated a statistically significant relationships ($p < .05$) between two out of five demographic variables (highest education of adult in household, $\chi^2(2) = 8.05$, $p = .018$ and income level of a child's household, $\chi^2(3) = 12.25$, $p = .007$) and the dependent variable. Also, in terms of directionality, both demographic variables seemed to be associated with the dependent variable. Specifically, it seemed as if a college or higher degree significantly related to overweight/obese status. As the levels of education increased, the percentage of study participants coded as overweight/obese decreased (healthy weight 53%, $n = 135$ versus overweight/obese status 42.7%, $n = 47$). Likewise, income level of a child's household seemed to be significantly related to overweight/obese status. Participants who reported having a 400% FPL or more seemed to have a lower percentage of study participants with overweight/obese status (healthy weight 42.9%, $n = 100$ versus overweight/obese status 25.4%, $n = 29$) than those reporting less than 400% FPL. Lastly, in terms of magnitude, the Cramer's V reflected small effects for both demographic variables highest education of adult in household and income level of a child's household (Cramer's V = 0.154 and Cramer's V = .188, respectively).

Table 5

Frequencies and Percentages for Demographic Variables by Weight Status

Variable	Healthy Weight *n*	Healthy Weight %	Overweight/Obese *n*	Overweight/Obese %	χ^2	*p*	Cramer's *V*
Race/Ethnicity							
White, Non-Hispanic	135	57.9[a]	64	56.1[a]	5.9	.115	.120
Black, Non-Hispanic	12	5.2[a]	1	0.9[b]			
Hispanic	33	14.2[a]	16	14.0[a]			
Other/Multi-racial, Non-Hispanic	53	22.7[a]	33	28.9[a]			
Sex of selected child					.24	.625	.026
Male	123	52.8[a]	57	50[a]			
Female	110	47.2[a]	57	50[a]			

(continued)

Frequencies and Percentages for Demographic Variables by Weight Status

Variable	Healthy Weight		Overweight/Obese				Cramer's
	n	%	*n*	%	χ^2	*p*	*V*
Highest education of adult in household					8.05	.018	.154
Less than High school/ High school or GED	39	17.0[a]	29	26.4[a]			
Some college or technical school	56	24.3[a]	34	30.9[a]			
College degree or higher	135	58.7[a]	47	42.7[b]			
Income level of a child's household (% FPL)					12.25	.007	.188
0-99	17	7.3[a]	15	13.2[a]			
100-199	36	15.5[a]	27	23.7[a]			
200-399	80	34.3[a]	43	37.7[a]			
400 or greater	100	42.9[a]	29	25.4[b]			

(continued)

Frequencies and Percentages for Demographic Variables by Weight Status

	Healthy Weight		Overweight/Obese				Cramer's
Variable	*n*	%	*n*	%	χ^2	*p*	*V*
Family structure of a child's household					3.14	.076	.101
Single parent	41	19.5[a]	28	28.6[a]			
Two parents	169	80.5[a]	70	71.4[a]			
Age of selected child					.140	.708	.020
10-12 years	69	29.6[a]	36	31.6[a]			
13-17 years	164	70.4[a]	78	68.4[a]			

Note. For each category, pairs of column proportions with different superscripts differed significantly, $p < .05$.

Research Questions 2 and 3

A chi-square analysis that examined which independent variable revealed a statistically significant association with the dependent variable (see Table 4). Consequently, there was no need to run a binary logistic regression to examine predictors that were the most significant at predicting childhood overweight/obese status. However, bivariate analysis between demographic and dependent variables (see Table 5) displayed statistically significant relationships between two of the demographic variables and the dependent variable. Variables highest education of adult in household and income level of a child’s household had statistically significant relationships with the dependent variable ($\chi^2(2) = 8.05$, $p < .018$, Cramer’s V = .154 and $\chi^2(3) = 12.25$, $p < .007$, Cramer’s V = .188, respectivelly). Considering that these variables might provide some information about demographic variables and the probability of childhood overweight/obese status, they were analyzed in the binary logistic regression model. The following section presents binary logistic regression examining the demographic variables highest education of adult in household and income level of a child’s household as predictors of overweight/obese status. This section answered Research Questions 2 and 3.

Research Question 2. Does the inclusion of a particular risk factor increase or decrease the probability of childhood overweight/obese status in Oklahoma?

Research Question 3. Does the exclusion of a particular risk factor increase or decrease the probability of childhood overweight/obese status in Oklahoma?

Reference group college degree or higher was selected to determine whether overweight/obese status for those with less than high school, high school or GED, or some college or technical school differed significantly in reference to those with a college degree or higher education. Reference group *income level of a child’s household based on the DHHS guideline of 400% FPL or more* was selected to determine whether overweight/obese status for households with income level less than 400% FPL differed significantly in reference to households income level at 400% FPL or more. Each reference group was selected to compare overweight/obese status based on the bivariate analysis results for highest education of adult in child’s household (as the levels of education increased, the percentage of study participants coded as overweight/obese decreased) and income level of a child's household (study participants who identified as having a 400% FPL or more percentages seemed to have a lower percentage of study participants with overweight/obese status) described earlier.

Table 6 presents a binary logistic regression analysis examining demographic variable income level of a child's household, with college or higher education level as the reference category, and demographic variable income level of a child's household, with households with income based on the DHHS guidelines of 400% FPL or more as the reference category. Logistic regression analyses indicated that the overall model was statistically significant, $\chi 2$ (5) = 14.69, $p < .05$ ($p = 0.012$). The Nagelkerke pseudo R^2 indicated that themodel accounted approximately 5.9% of the total variance in the dependent variable oveweight/obese status. Weight status classification for the cases based on a classification cutoff value of .500 for predicting membership in the overweight/obese group was low, with an overall prediction of overweight/obese status rate of 67.6% and correct prediction rates of 0.0% for overweight/obese weight status and 100% for healthy weight only. In terms of individual predictors, reference to those with income level of a child's household based on the DHHS guidelines of 400% FPL or more, those with income level of a child's household between 0 to 99% FPL and 100 to 199% FPL were over two times (OR = 2.434, 95% CI=1.012–5.865 and OR = 2.219, CI = 1.106–4.452) more likely to have children who had an overweight/obese status.

Table 6

Binary Logistic Regression Analysis Results (n = 347)

Variable	B	S.E.	Wald χ^2	df	Sig.	Exp(B) OR	95% CI
Highest education of adult in the household							
Less than HS/HS or GED	.435	.326	1.779	1	.182	1.545	.815–2.929
Some college or technical	.390	.287	1.853	1	.173	1.477	.842–2.591
Income level of child's household (% FPL)							
0–99	.890	.448	3.946	1	.047	2.434	1.012–5.865
100–199	.797	.355	5.034	1	.025	2.219	1.106–4.452
200–399	.461	.294	2.458	1	.117	1.586	.891–2.823

Note. The dependent variable was *overweight/obese status* with college degree of higher and income level of child's household 400% FPL or more as reference groups. For Model: $\chi2$ (6) = 14.69, $p < .05$ ($p = .023$).

CHAPTER V

DISCUSSION

Introduction

This chapter is divided into five sections. The first section contains a summary of the main findings from this study. The second section consists of a discussion of the present study's findings as they pertain to other researchers' findings on family meals, sleep, and media use as predictors of childhood overweight/obese status. The third section highlights the strenghts and limitations of this study. The fourth section contains implications and recommendations for future research. Finally, the last section includes recommendations for health education and health promotion practice, followed by a conclusion.

Summary of Findings

The alarming and sustained prevalence of childhood obesity in the US continues to generate research studies that seek to not only examine its causes, but also to suggest prevention approaches. Despite previous and current public health interventions to address the prevalence of children who are overweight and obese in the US, Oklahoma ranks the sixth worst state in obesity with a third of children between 10 to 17 years being overweight or obese and 1 in 5 high school students being obese (Shape Your Future, 2018; The State of Obesity, 2019). Moreover, research that predicts the most significant risk factors of children who are overweight/obese in Oklahoma is lacking, leaving a gap for prevention and management research. In attempts to fill this gap and to inform future public health prevention and management strategies of childhood overweight/obese status, the present study examined the risk factors that significantly predict childhood overweight/obese status within the home environment.

This study used secondary data from the 2016 National Survey of Children's Health dataset to explore activities that occur in a home environment, namely family meals, sleep, and media use, as predictors of the overweight/obese status among children between 10–17 years of age to determine the most significant risk factors in predicting overweight/obese status in children who live in Oklahoma. Statistical analyses were conducted on a representative subsample of 347 (46.5%) participants who responded to the measure of interest (overweight/obese status). The study attempted to answer the three research questions: (1) If childhood overweight/obesity status can be predicted from the 2016 NSCH, which risk factors (family meals, sleep, and media use) are the most significant at predicting childhood overweight/obese status in Oklahoma? (2) Does the inclusion of a particular risk factor increase or decrease the probability of childhood overweight/obese status in Oklahoma? (3) Does the exclusion of a particular risk factor increase or decrease the probability of childhood overweight/obese status in Oklahoma?

According to this study's findings (see Table 4), none of the predictors of interest (family meals, bed time, and media use) related to the dependent variable at a statistically significant level ($p < .05$; family meals $p = .477$; sleep - bed time $p = .824$; sleep - past week sleep average $p = .212$; sleep - hours of sleep $p = .281$; media use - daily average time spent watching television, videos, or playing video games $p = .513$, and media use -

daily average use of computer, cellphone, or electronic devices p = .581) to be included in a binary logistic regression analysis that would model the dependent variable as a function of predictor variables. Consequently, all null hypotheses were accepted. Table 7 summarizes the null hypotheses based on the present study's results:

Table 7

Summary of Results

Null Hypothesis ($\boldsymbol{H_0}$)	Reject or Accept
$\boldsymbol{H_{01}}$. Family meals, sleep, and media use will be neither predictive nor protective of childhood *overweight/obese status* in Oklahoma.	Accept
$\boldsymbol{H_{02}}$. Family meals, sleep, and media use will not significantly differ between normal weight children and children who are overweight/obese in predicting childhood *overweight/obese status* in Oklahoma.	Accept
$\boldsymbol{H_{03}}$. Family meals, sleep, and media use will not significantly differ by age groups (10-12 years and 13-17 years) in predicting childhood *overweight/obese status* in Oklahoma.	Accept
$\boldsymbol{H_{04}}$. Family meals, sleep, and media use will not significantly differ between children who are male and female in predicting childhood *overweight/obese status* in Oklahoma.	Accept

Regarding predictors of interest, the highest proportion of participants ate a meal together for 4 to 6 days during the past week (37.2%; *n* = 129). Three survey items were used to measure variable *sleep* (bed time, past week sleep average, and hours of sleep). The majority of participants reported having children who usually or always went to bed at the same time on weeknights (84.7%; *n* = 294), who slept recommended age-appropriate hours (62.8%; *n* = 218), and who slept for eight hours or more per night during the past week (72.3%; *n* = 251). Lastly, more participants reported that children spent an average of one to three hours watching television, videos, or playing video games daily (73.5%; *n* = 255) and an average of 1 to 3 hours with a computer, cellphone, or electronic device (65.4.0%; *n* = 227). With respect to the dependent variable, more than half of respondents indicated a healthy weight status for children (67.1%; *n* = 233) and about one third were overweight/obese (32.9%; *n* = 114).

Discussion

Based on this study's results, none of the tested independent variables family meals, sleep, and media use was determined to be the most significant risk factor in predicting childhood overweight/obese status in Oklahoma. That is, family meals, sleep, and media use were neither predictive nor protective of childhood overweight/obese status in Oklahoma. Further, they did not significantly differ by weight status (normal vs overweight/obese status), by age groups (10–12 years and 13–17 years), and by gender (male and female) in predicting childhood overweight/obese status in Oklahoma. While predictors of interest (family meals, sleep, and media use) did not exhibit statistically significant relationships with the outcome variable (overweight/obese status), preliminary analyses and primary analyses on two demographic variables revealed interesting associations between variables. Two demographic variables, the highest education of adult in the household, and income level of a child's household, showed a significant association with childhood overweight/obese status. As the levels of education and income increased, childhood overweight/obese status decreased. Income levels seemed to be more predictive of overweight/obese status than the highest education levels. In household with income levels between 0–99% FPL and between 100–199%, children were over two times more likely to have an overweight/obese status than in households that reported income levels at 200% FPL or above. On the contrary, childhood overweight/obese status decreased in households that reported 400% FPL or more. These findings support previous research studies that suggest a decrease in the prevalence of obesity among adolescents from well-educated and high-income families, compared to those from less-educated and low-income families (Baer et al., 2018; Frederick et al., 2014; Nguyen et al., 2015). With attention to predictors (family meals, sleep, and media use), the highest proportion of participants ate a meal together for 4 to 6 days during the past week (37.2%; n = 129). The majority of participants reported having children who usually or always went to bed at the same time on weeknights (84.7%; n = 294), who slept recommended age-appropriate hours (62.8%; n = 218), and who slept for eight hours or more per night during the past week (72.3%; n = 251). Lastly, more participants reported that children spent an average of 1 to 3 hours watching television, videos, or playing video games daily (73.5%; n = 255) and an average of 1 to 3 hours with a computer, cellphone, or electronic device (65.4.0%; n = 227). With respect to the dependent variable, more than half of respondents indicated a healthy weight status for children (67.1%; $n = 233$), and about one third were overweight/obese (32.9%; $n = 114$).

The explanation for these findings could be either that all predictors equally predict childhood overweight/obese status or that other factors related to the study design affected the results and will be further discussed in the limitations of the study. Findings from this study differ from other studies that examined family meals, sleep or media use as predictive or protective single factor of childhood overweight/obese status. In other words, previous studies on predictive or protective factors of childhood overweight/obese status focused on each factor in relation to the outcome (overweight/obese status), but not on which factor was the most significant in predicting childhood overweight/obese status. Nevertheless, the present study's preliminary analyses of family meals, sleep, and media use revealed that none of the factors related to the dependent variable, overweight/obese status, at a statistically significant level ($p < .05$) for inclusion in the logistic regression model as they would be regarded as occurring by chance.

Family Meals

In the present study, family meals were measured using the number of days all family members who live in the household ate a meal together (0 = *No days*, 1 = *1–3 days*, 2 = *4–6 days*, 3 = *Everyday*; CAHMI & DRCCAH, 2018). The analysis of the relationship between family meals and overweight/obese status, using Chi-square, revealed no statistical relationship between family meals and childhood overweight/obese status. Since the predictor family meals did not meet the criteria ($p < .05$) for inclusion in the logistic regression to model the dependent variable as a function of predictor family meals, the present study's analyses determined that family meals were not a protective nor a predictive factor in childhood overweight/obese status in Oklahoma. Further, family meals did not significantly differ between normal weight children and children who are overweight/obese in predicting childhood overweight/obese status in Oklahoma. Again, family meals did not significantly differ by age groups (10–12 years and 13–17 years), nor did it significantly differ between male and female children in predicting childhood overweight/obese status in Oklahoma.

Unlike the present study, some studies on the association between family meals and health outcomes have found significant associations between family meals and reduced likelihood of overweight/obese status (Berge et al., 2015; Berge et al., 2017; Berge et al., 2018; Berge et al., 2019; Dallaker & Hertwig, 2019; Dwyer, Oh, Patrick, & Hennessy, 2015; Gunther et al., 2019; Lee, Lee, & Park, 2016) while others have proposed mixed results (Berge et al., 2017; Dwyer et al., 2015; Gunther et al., 2019; Lee et al., 2016). With attention to positive associations between family meals and health outcomes, numerous studies have identified the benefits of family meals for both parents/caregivers and their children (Berge et al., 2015; Berge et al., 2017; Berge et al., 2019; Dwyer et al., 2015, Jones, 2018; Lee, et al., 2016). For instance, some of the benefits of regular family meals include higher frequency of fruits and vegetables consumption, variety in the types of foods consumed, emotional connection and support among family members, increased sense of security for younger children, opportunities for parents/caregivers to model healthy behaviors, and recognition of satiety clues during family meals (Berge et al., 2015; Brooks, 2017; Caldwell et al., 2018; Dallaker & Hertwig, 2019; Jones, 2018; Lee, et al. 2016). In a meta-analysis of family meals, researchers found a significant association between family meals and each of the studied outcomes in children, namely, lower body mass index (r = .05), more healthy eating (r = .10) and less unhealthy eating (r = -0.4; Dallaker & Hertwig, 2019, p. 1137). Additionally, they identified five family meals components that were positively associated with better children's nutrition such as turning the television off during meals (r = .09), parents' modeling healthy eating (r = .12), higher food quality (r = .12), positive atmosphere (r = .13), involving children in meals preparation (r = .08), and longer meal duration (r = .13) (Dallaker & Hertwig, 2019, p. 1142). Considering the positive association between family meals and the risk of childhood overweight/obese status, interventions should address factors that increase and barriers that decrease the frequency of family meals.

Specific factors have been attributed to the differences in outcomes that led to mixed findings or inconsistencies in other studies. Factors such as differences in the definition of family meals, the types of meals that are assessed (breakfast, lunch or dinner), the person who reports on family meals during interviews (parent/caregiver or child), the number of people who participate in the meal, sociodemographic variables studied, and other methodological differences across studies explain some of the discrepancies in findings (Dwyer et al., 2015; Gunther et al., 2019; Lee et al., 2016; Valdés et al., 2013). For example, in their systematic review about the frequency of family meals and childhood overweight, Valdés et al. (2013, p. e11) attributed inconsistencies in the relationship between family meals and childhood overweight to the "lack of standardization" in the attributes of family meals (location, number of people, and timing), the "types of measurement tools" used to assess the frequency of family meals (In-person or self-administered interviews, children or parents, reference period of meals' consumption, frequency), and "missing information" on the key components of family meals (length, nutritional value, presence or absence of media use, sociodemographic characteristics, and physical activity- and diet-related variables).

Some studies that target minorities and populations with low socioeconomic status have also found some inconsistencies in their findings (Berge et al., 2017; Dwyer et al., 2015; Gunther et al., 2019). During an intervention on families from diverse racial background and low socioeconomic status, researchers found "no effects on daily consumption of fruits, vegetables, sugar-sweetened beverages fruits consumption, and diet quality due to low response rate after the intervention and follow up" (Gunther et al., 2019, p. 13). Researchers cited barriers such as low response due to difficulty in contacting participants after the intervention, which is one of the prevailing barriers most low socioeconomic populations (Gunther et al., 2019). This barrier could be addressed by relying on community partners to provide updates on participants' information, in case they changed their address (Gunther et al., 2019). Also, methods (5-step multi-pass dietary recall from the U.S. Department of Agriculture) used to obtain diet recall (in-person and on the phone) seemed taxing to participants (Gunther et al., 2019). The use of technology in the form of mobile phone applications that digitally capture dietary information, provided that participants could easily access them via cellphone, might have alleviated the burden of in-person and phone calls to obtain information on diet recall (Gunther et al., 2019).

While many studies demonstrate a protective role of family meals against the development of overweight/obesity in adolescents (Berge et al., 2015; Berge et al., 2017; Dwyer et al., 2015; Jones, 2018), other studies do not. Several factors contribute to the differences in studies outcomes. Thus, the present study's findings on family meals as predictor of childhood overweight/obese status should be interpreted with caution and considering its limitations, which will be discussed later.

Sleep

The present study investigated the adequate amount of sleep, which represented "the number of nights a child sleeps for the recommended duration, based on the child's age and age-related recommendations from the NSF (CAHMI & DRCCAH, 2018). Variables bed time, hours of sleep, and past week sleep average measured sleep in this study. This study's results indicated that bed time (p = .824), hours of sleep (p = .281), and past week sleep average (p = .281) did not significantly affect childhood overweight/obese status in the analyzed subsample. Since sleep did not meet the criteria (p<.05) for inclusion in the logistic regression to model the dependent variable as a function of predictor sleep, it was concluded that sleep did not protect children from the risk of, nor did it predict childhood overweight/obese status in the studied sample. Furthermore, sleep did not significantly differ between normal weight children and children who are overweight/obese in predicting childhood overweight/obese status in

Oklahoma. Also, sleep did not significantly differ by age groups (10–12 years and 13–17 years), nor did it significantly differ between male and female children in predicting childhood overweight/obese status in Oklahoma. Consequently, sleep was determined, in this study, to not be the most significant factor in predicting childhood overweight/obese status in Oklahoma.

Contrary to the present study, others have found that sleep duration and quality affect childhood weight status through physiological and behavioral changes that, in turn, affect energy intake, food choices, and physical activities (Baiden, Tadeo, & Peters, 2019; Chaput & Dutil, 2016; Gohil & Hannon, 2018; Hart et al., 2017; Narcisse et al., 2019; Robinson et al., 2017). Physiological changes such as a decrease in leptin, a hormone that regulates satiety, and an increase in ghrelin, a hormone that signals hunger, affect appetite by increasing food intake (Gohil & Hannon, 2018; Hart et al., 2017; NSF, 2018b; Ogilvie & Patel, 2017). Behavioral changes associated with reduced sleep duration and quality include decreased physical activities and increased consumption of unhealthy foods (Baiden et al., 2019; Chaput & Dutil, 2016; Gohil & Hannon, 2018; Narcisse et al., 2019).

With the exception of a few (Hart et al., 2017; Klingenberg et al., 2012; Krietsch, Chardon, Beebe, & Janicke, 2019; Robinson et al., 2017), most research studies examining the influence of sleep on the risk of childhood overweight/obese status have demonstrated a negative association between sleep duration and the risk of obesity (Baiden et al., 2019; Chaput & Dutil, 2016; LeBourgeois et al., 2017; Robinson et al., 2017; Widome et al., 2019). For the most part, inconsistencies (Hart et al., 2017;

Robinson et al., 2017) or no clear determination of causation in research findings (Gohil & Hannon, 2018) are due to differences in demographics, variations in the amount of sleep (Reutrakul & Cauter, 2018), and methodological or statistical issues (Krietsch et al., 2019). Widome et al. (2019) studied the influence of sleep duration on weight-related behaviors in a sample of 2,134 adolescents. Their study's findings demonstrated negative associations between reduced sleep hours and an increase in the consumption of unhealthy foods, and between reduced sleep hours and a decrease in physical activities, which are risk factors for childhood overweight/obese status. Findings from other research studies also suggested a negative association between insufficient sleep and the risk of overweight/obese status (Baiden et al., 2019; Chaput & Dutil, 2016; Hart et al., 2017; Narcisse et al., 2019; Reid Chassiakos, 2017; Robinson et al., 2017; Widome et al., 2019).

While Hart et al. (2017) found a similar negative association between the duration of sleep and weight-related behaviors, they also reported mixed findings from their study, as a previous study by Klingenberg et al. (2012). As a matter of fact, decreased sleep led to more activity counts during the day (Hart et al., 2017) due to the inability to sleep for long hours (Klingenberg et al., 2012). As pointed out by Hart et al. (2017), the increase in activity counts did not compensate for energy expenditure because children ended up increasing caloric intake, leading to a risk of weight gain despite increased activity counts. With attention to research on the influence of sleep duration and the risk of overweight/obese status, it appears that shortened sleep hours tend to increase high caloric food intake and decrease physical activities in this population, which contrasts findings from the present study. For this reason, the present study's findings on sleep as a predictor of childhood overweight/obese status should be interpreted with caution and considering its limitations, which will be discussed in the strengths and limitations section.

Media Use

The present study analyzed media use, which measured the daily average of time spent watching television/videos or playing video games (p = .513) and the time spent with a computer, cellphone, or electronic handheld video game, and other electronic devices (p = .581), and doing things other than schoolwork (CAHMI & DRCCAH, 2018). Because media use did not meet the inclusion criteria (p = .05) in the logistic regression model that would predict childhood overweight/obese status, findings from the present study, in contrast to other research studies, concluded that media use was not a protective nor a predictive factor in childhood overweight/obese status in Oklahoma. Further, media use did not significantly differ between normal weight children and children who are overweight/obese in predicting childhood overweight/obese status in Oklahoma. Moreover, media use did not significantly differ by age groups (10–12 years and 13–17 years), nor did it significantly differ between male and female children in predicting childhood overweight/obese status in Oklahoma.

Unlike findings from the present study, other studies have suggested that media use, in the form of television, computers, or electronic devices have been associated with many adverse health outcomes including poor sleep quality and obesity (Baiden et al.

2019; LeBourgeois et al., 2017; Reid Chassiakos et al., 2016; Robinson et al., 2017; Tanskey et al., 2018). Some of the attributes that relate media use to the risk of childhood overweight/obese status include reduced time for physical activities, consumption of unhealthy foods as a result of exposure to advertisements (Reid Chassiakos et al., 2016; Robinson et al., 2017; Tanskey et al., 2018), uncertainty in satiety cues due to distraction from food/beverages commercials (Lee et al., 2018; Robinson et al., 2017), and sleep deprivation affect appetite- and satiety-regulating hormones (Lee et al., 2018; Robinson et al., 2017). Given these points, findings of media use as predictor of childhood overweight/obese status, in the present study, should be carefully interpreted considering the study's limitations, which will be discussed in the strengths and limitations section.

Strengths and Limitations

This study's strengths include a nationally representative sample of households, and a large sample size to generate estimates for Oklahoma. Furthermore, the study is a contributor in the area of childhood overweight/obese status prevention because it is, based on current knowledge, the first attempt to examine factors within the home environment that most significantly predict childhood overweight/obese status in Oklahoma and sheds light on the relevance of data collection methods on research outcomes. This study supports the increasing need of family-based approaches as an effective method for the prevention of childhood overweight/obese status (Alulis & Grembowski, 2017; Ash, Agaronov, Young, Aftosmes-Tobio, & Davison et al., 2017; Dinkel et al., 2017; Fulkerson et al., 2015; Jordan, Graham, Berkel, & Smith, 2019;

Zoellner et al., 2017). For example, in the Healthy Home Offerings via the Mealtime Environment Plus study, a 10-month prevention- and family-focused randomized control trial that promoted healthier lifestyle and prevented excess weight gain among 8–12 years old children, researchers directly measured nutrition and weight-related outcomes (Fulkerson et al., 2015). While results indicated that the intervention effect on body mass index z-scores was not statistically significant, researchers observed “modest and promising decreases in weight gain at post-intervention” (Fulkerson et al., 2015, p. 9). Further, findings also call for researchers’ attention to collecting both quantitative and qualitative data that proportionately represent demographic and socioeconomic groups being studied. In this study, most of the sub-sample consisted of White ethnic group, educated and college or higher level of education participants. Also, quantitative data from this subsample were re-coded into dichotomous variables and other variables were collapsed into smaller categories due to low cell values, which might have led to current findings. Moreover, it confirms that education and income levels affect children’s weight outcomes.

This study has several limitations. First, the cross-sectional nature of the study rules out any inferences of causality, as well as underreporting and sampling, recall, or non-response bias from respondents. Second, more than half of the data needed to be removed from the analysis due to missing information. Third, for privacy reasons, the public NSCH database did not include information about children’s weight and height, which prevented the use of body mass index-for-age percentile to determine childhood, as continuous body mass index scores are more sensitive to analyses than categorical values (Fatima, Doi, & Mamun, 2015). Fourth, possible risks of bias and measurement error due to self-reported data and non-responses to the measures of interest might have led to no statistically significant results, thus weakening the magnitude of findings (LeBourgeois et al., 2017). Lastly, social desirability bias, which is the extent to which research participants answer to survey questions in a way that seems socially acceptable or as an aspiration to what they want to do or aspire to, may have led to misclassification of children's weight status due to its under- or overreporting by parents or caregivers (Cullinan & Cawley, 2017; Koning et al., 2018). Hence, the present study supports childhood overweight/obese status research focusing on factors, within the home environment, that most significantly predict childhood overweight/obese status in Oklahoma. This study's limitations present an opportunity for the improvement of future research with regards to research design for the most affected populations.

Implications and Recommendations for Future Research

A growing body of research continues to document the impact of family-based approaches in childhood obesity prevention (Alulis & Grabowski, 2017; Ash et al., 2017; Dinkel et al., 2017; Jordan et al., 2019; Zoellner et al., 2017). This study presents the first exploration of risk factors, within the home environment by investigating those that significantly increase the risk of childhood overweight/obese status to build the evidence base that will guide prevention strategies at home. This investigation adds to existing literature by highlighting the need to expand research methodology for national surveys by including population-based longitudinal studies that include both qualitative and quantitative research of the most significant risk factors of childhood overweight/obese status. The study recognizes that national surveys contribute to research through data collection methods that are subject to rigorous guidelines and through the release of data to researchers for further studies. Also, the study notes that a number of factors, outside the control of data collection methods, may affect the quality of data and their subsequent analyses. For instance, the lack of responses to the measure of interest led to the exclusion of participants who did not meet the criteria in this study.

Other factors like respondents' relocation, lack of internet or telephone access, lack of time, social desirability biases, and other non-response biases may affect the quality of data. With that in mind, incorporation of both qualitative and quantitative data collection methods in national surveys may lessen those biases. Qualitative research methods like focus group discussions with family members, objective anthropometric measurements, diet recall by trained professionals, and direct observation can also be incorporated for in-depth analysis of the most significant factors that increase the risk of childhood overweight/obese status. Experimental research might also expound on the most significant factors that increase the risk of childhood overweight/obese status and possibly establish cause and effect relationships, assess interventions, and identify preceding components that affect response to exposure or the structure of such relationships. For example, an experimental study compares outcomes in participants randomly assigned to a group in which the quality and frequency of family meals, sleep, and media use meets criteria that have been shown to decrease the risk of childhood overweight/obese status (intervention group) with a group that does not meet those criteria (control group) to study whether exposure affects the outcome (overweight/obese status). In a like manner, an observational study, such as a case-control study that assesses how family meals, sleep, and media use affect childhood overweight/obese status by comparing exposure histories of children who are overweight/obese to those who are not overweight/obese to identify likely risk factors for childhood overweight/obese status may also identify factors that might significantly affect childhood overweight/obese status.

In both qualitative and quantitative designs, researchers should use a standardized definition of family meals, sleep, and media use. In this case, family meals should include the number of people who are present during each meal and researchers should use validated questionnaires with trained interviewers, take into account seasonal variability in family meals, and collect information about confounding factors that may affect family meals (Valdès et al., 2013). For instance, in populations that may experience more barriers to family meals, Dwyer et al. (2015, pp. 127–128) suggested "delivering interventions remotely or in the work place." Dwyer et al. (2015, pp 127–128) also suggested "tailoring interventions by family characteristics (single-headed or dual-headed)" and by the "types of barriers experienced by each family (food cost, creative meals, and child involvement during meal preparation)". Also, standard definitions should be used for sleep and media use in which researchers should include the location where sleep occurs (own bedroom, shared, living room, etc), in addition to other components used in the present studies. For media use, in addition to the total hours spent, researchers should include the location and time when it occurs (e.g.,during meal time; Valdès et al., 2013). Besides the use of standardized definitions, researchers should be cognizant and mindful of how people's perception of the questions might affect their responses and incorporate other validation methods to reduce social desirability bias (Cullinan & Cawley, 2017; Koning et al., 2018). For example, researchers could validate parents' and children's answers by using objective measurements such as anthropometric measurements, plate waste assessment, physical activity, or sleep monitoring devices, etc.

In addition, researchers should seek to increase participation and representation of underrepresented demographic and social groups during data collection. In the present study, the majority of participants were male (51.9%; *n* = 180) and White Non-Hispanic (57.3%; *n* = 199), and a greater number of adults had a college or a higher education level (52.4%; *n* = 182). By comparison, participation from Non-Hispanic Black population was lower (3.7%) than the 2016 population estimates (7.1%). In 2016, Oklahoma had an estimated population of 3,875,589 of which the majority was White (72.9%) and female (50%; U.S.Census, 2020). Keeping in mind that each research study includes strengths and limitations, researchers should use limitations as opportunities to be addressed in future studies and strengths as opportunities for comparative studies on the most significant risks on childhood overweight/obese status to guide practice on prevention and management of childhood overweight/obese status.

Recommendations for Health Education and Health Promotion Practice

Given that a growing body of research between each factor investigated in the present study (family meals, sleep, and media use) and the risk of childhood overweight/obese status continues to suggest an association between each factor and the risk of childhood overweight/obese status, and although the present study's findings suggested non-significant results between predictors of interest (family meals, sleep, and media) and the dependent variable (overweight/obese status; see Table 4), the present study has identified 10 recommendations from a pubic health perspective to promote overall health. Health education and promotion practitioners should

(1) take every opportunity to talk to families about the effect of family meals, sleep, and media use on health;

(2) continue to provide realistic recommendations and resources to parents or caregivers to address challenges related to family meals planning, preparation and frequency; bedtime routine to promote healthy sleep duration and quality; the consequences of media use on health and how to consistently clarify media use expectations for the whole family;

(3) highlight protective behaviors that promote family meals, regular sleep time and duration, and healthy media use in children and adolescents;

(4) encourage parents or caregivers to seek help early for concerns related to childhood weight management or issues related to meals, sleep or media use in their children;

(5) encourage parents or caregivers to not give up in their pursuit of childhood weight management despite challenges that may emerge during treatment or management;

(6) continue to conduct more interdisciplinary research on modifiable factors that increase the risk of childhood overweight/obese status;

(7) continue to conduct interdisciplinary research on practical interventions that promote protective behaviors against the risk of childhood overweight/obese status;

(8) assess the feasibility of such interventions on different populations;

(9) continue to improve their health education and health promotion competence to stay informed about the changes in research on prevention and management of childhood overweight/obese status, and;

(10) continue to acquire skills in the application and integration of theories from other disciplines to effectively intervene in the prevention and management of childhood overweight/obese status.

Conclusion

The results of this study indicate that family meals, sleep, and media use do not significantly predict childhood overweight/obese status in Oklahoma. These findings differ from studies on childhood obesity and they should be carefully considered in light of similar studies. Many research studies on family meals, sleep, and media use as predictors of childhood overweight/obesity focus on the relationship between a single predictor (or a combination of predictors) and childhood overweight/obese status or the recognition of a single predictor or a combination of predictors as risk and protective factors within home environments (Berge et al., 2015, 2017, 2018; Dube et al., 2017; Fatima et al., 2015; Hart et al., 2017; Jones, 2018; LeBourgois et al., 2017; Lee et al., 2016; Lewin et al., 2016; Rogers et al., 2017). Most of those studies do propose a relationship between predictors and childhood overweight/obese status, with findings that suggest an inverse relationship between predictor(s) and overweight/obese status (Berge et al., 2015, 2017, 2018; Dube et al., 2017; Fatima et al., 2015; Hart et al., 2017; Jones, 2018; LeBourgois et al., 2017; Lee et al., 2016; Lewin et al., 2016; Rogers et al., 2017) or bidirectional relationships (LeBourgois et al., 2017). Alongside such findings, researchers also note many limitations such as limited overall interactions by race/ethnicity, sex, socioeconomic status and age, and other limitations such as self-reported body mass index, cross-sectional designs, non-response bias (Berge et al., 2015, 2018; Dube et al., 2017; Hart et al., 2017; Jones, 2018; Lee et al., 2016), lack of randomization (Rogers et al., 2017), and not providing information about daytime and nighttime sleep (Fatima et al., 2015). Nevertheless, research on the risk factors that significantly predict childhood overweight/obese status warrants investigations, as findings may guide prevention efforts.

REFERENCES

Alulis, S., & Grabowski, D. (2017). Theoretical frameworks informing family-based child and adolescent obesity interventions: A qualitative meta-synthesis. *Obesity Research & Clinical Practice*, *11*, 627–639. doi:10.1016/j.orcp.2017.08.001

Annesi, J. J., Walsh, S. M., Greenwood, B. L., Mareno, N., & Unruh-Rewkowski, J. L. (2016). Effects of the youth fit 4 life physical activity/nutrition protocol on body mass index, fitness and targeted social cognitive theory variables in 9- to 12-year-olds during after-school care. *Journal of Paediatrics and Child Health*, *53*,365–373. doi:10.1111/jpc.13447

Apple, R. D. (2015). Childhood obesity in America: Biography of an epidemic/The nature of childhood: An environmental history of growing up in America since 1865. *Journal of American History*,*102*(3), 897–899. doi:10.1093/jahist/jav522

Archer, E., Lavie, C. J., & Hill, J. O. (2018). The contributions of 'diet', 'genes', and physical activity to the etiology of obesity: Contrary evidence and consilience. *Progress in Cardiovascular Disease*, *61*, 89–102. doi:10.1016.j.pcad.2018.06.002

Ash, T., Agaronov A., Young, T., Aftosmes-Tobio A., & Davison, K. K. (2017). Family-based childhood obesity prevention interventions: A systematic review and quantitative content analysis. *International Journal of Behavioral Nutrition and Physical Activity*, *14*, 1–12. doi:10.1186/s12966-017-0571-2

Baer, T. E., Scherer, E. A., Richmond, T. K., Fleeger, E. W., & Hassan, A. (2018). Food insecurity, weight status, and perceived nutritional and exercise barriers in an urban youth population. *Clinical Pediatrics*, *57*, 152–160. doi: 10.1177/0009922817693301

Bagherniya, M., Sharma, M., Mostafavi, F., & Keshavarz, A. S. (2015). Application of social cognitive theory in predicting childhood obesity prevention behaviors in overweight and obese Iranian adolescents. *International Quarterly of Community Education*, *35,* 133147. doi: 10.1177/0272684X15569487

Baiden, P., Tadeo, S. K., & Peters, K. E. (2019). The association between excessive screen-time behaviors and insufficient sleep among adolescents: Findings from the 2017 youth risk behavior surveillance system. *Psychiatry Research*, *281*, 1–8. doi:10.1016/j.psychres.2019.112586

Bandura, A. (1986). *Social foundations of thought an action: A social cognitive theory.* Englewood Cliffs, NJ: Prentice Hall.

Bassett, D. R., John, D., Conger, S. A., Fitzhugh, E. C., & Coe, D. P. (2015). Trend in physical activity, and sedentary behaviors of United States youth. *Journal of Physical Activity and Youth*, *12*, 1102–1111. doi:10.1123/jpah.2014-0050

Berge, J. M., Wall, M., Hsueh, T., Fulkerson, J. A., Larson, N., & Neumark-Sztainer, D. (2015). The protective role of family meals for youth obesity: 10-year longitudinal associations. *The Journal of Pediatrics*, *166*, 296–301. doi:10.1016/j.jpeds.2014.08.030

Berge, J. M., Trofholz, A., Tate, A. D., Beebe, M., Fertig, A., Miner, M. H., …Neumark-Sztainer, D. (2017). Examining unanswered questions about the home environment and childhood obesity disparities using an incremental,mixed-methods, longitudinal study design: The family matter study. *Contemporary Clinical Trials*, *62*, 61–76. doi: 10.1016/j.cct.2017.08.002

Berge, J. M., Beebe, M., Smith, M. C-M., Tate, A., Trofholz, A., & Loth, K. (2019). Ecological momentary assessment of the breakfast, lunch, and dinner family meal environment in racially/ethnically diverse and immigrant households. *Journal of Nutrition Education and Behavior, 51*, 658–676. doi:10.1016/j.jneb.2019.03.002

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

Boots, S. B., Tiggemann, M., Corsini, N., & Mattiske, J. (2015). Managing your children's snack food intake: The role of parenting style and feeding strategies. *Appetite*, *92*, 94–101. doi:10.1016/j.appet.2015.05012

Bronfenbrenner, U. (1977). Toward an experimental ecology of human development. *American Psychologist*, *32*, 513–531. doi:10.1037/0003-066X.32.7.513

Bronfenbrenner, U. (1986). Ecology of the family as a context for human development: Research perspectives. *Developmental Psychology*, *22*, 723–742. doi:10.1037/0012-1649.22.6.723

Brooks, L. (2017). Examining the power of family meals as a protective factor in childhood and adolescent obesity. *Journal of the Academy of Nutrition and Dietetics*, *117,* A45–A45. doi: 10.1016/j.jand.2017.06.122

Caldwell, A. R., Terhorst, L., Skidmore, E. R., & Bendixen, A. (2018). Is frequency of family meals associated with fruits and vegetables intake among preschoolers? A logistic regression analysis. *Journal of Human Nutrition and Dietetics, 31*, 505–512. doi:10.1111/jhn.12531

Camp, N. L., Robert, R. C., Nash, J. E., Lichtenstein, C. B., Dawes, C., & Patterson, K. (2017). Modifying provider practice to improve assessment of unhealthy weight and lifestyle in young children: Translating evidence in a quality improvement initiative for at-risk children. *Childhood Obesity, 13*, 173–181. doi:10.1089/chi.2016.0124

Centers for Disease Control and Prevention. (n.d.). *High school YRBS*. Retrieved from https://nccd.cdc.gov/youthonline/App/Results.aspx?LID=OK

Centers for Disease Control and Prevention. (2015). *About child & teen body mass index.* Retrieved from https://www.cdc.gov/healthyweight/assessing/bmi/childrens_bmi/about_childrens_bmi.html

Centers for Disease Control and Prevention. (2016). *Nutrition, physical activity, & obesity data & statistics.* Retrieved from https://www.cdc.gov/healthyyouth/data/topics/npao.htm

Centers for Disease Control and Prevention. (2017). *The obesity epidemic and United States Students.* Retrieved from https://www.cdc.gov/healthyyouth/data/yrbs/pdf/2017/2017_US_Obesity.pdf

Centers for Disease Control and Prevention. (2018a). *Prevalence of overweight, obesity, and severe obesity among children and adolescents aged 2–19 years: United States, 1963–1965 through 2015–2016.* Retrieved from https://www.cdc.gov/nchs/data/hestat/obesity_child_15_16/obesity_child_15_16.htm

Centers for Disease Control and Prevention. (2018b). *Trends in the prevalence of obesity and dietary behaviors national YRBS: 1991–2017.* Retrieved from https://www.cdc.gov/healthyyouth/data/yrbs/pdf/trends/2017_obesity_trend_yrbs.pdf

Centers for Disease Control and Prevention. (2018c). *Childhood obesity over time: Percentage of high school students who were obese, selected U.S. states, Youth Behavior Survey, 2017.* Retrieved from https://www.cdc.gov/healthyyouth/data/topics/npao.htm

Centers for Disease Control and Prevention. (2018d). *Prevalence of childhood obesity in the United States.* Retrieved from https://www.cdc.gov/obesity/data/childhood.html

Chaput, J-P., & Dutil, C. (2016). Lack of sleep as a contributor to obesity in adolescents: Impact of eating and activity behaviors. *International Journal of Behavioral Nutrition & Physical Activity*, *13*, 1–9. doi:10.1186/s12966-016-0428-0

Child and Adolescent Health Measurement Initiative. (2017). *2016 National survey on children's health (NSCH): Fast facts.* Retrieved from http://childhealthdata.org/docs/default-source/nsch-docs/2016-fast-facts_11-02-17.pdf?sfvrsn=27ee5417_2

Child and Adolescent Health Measurement Initiative & Data Resource Center for Child and Adolescent Health. (2018). *2016 National survey of children's health: Child* *and family health measures and subgroups, SPSS codebook, version 2.0.* Retrieved from http://childhealthdata.org/

Cruwys, T., Bevelander, K. E., & Hermans, R. C. J. (2015). Social modeling of eating: A review of when and why social influence affects food intake and choice. *Appetite*, *86*, 3–18. doi:10.1016/j.appet.2014.08.035

Cullinan, J., & Cawley, J. (2017). Parental misclassification of child overweight/obese status: The role of parental education and parental weight status. *Economics and Human Biology*, *24*, 92–103. doi:10.1016/j.ehb.2016.11.001

Curtis, D., Fuller-Rowell, T. E., Doan, S. N., Zgierksa, A., & Ryff, C. (2016). Racial and socioeconomic disparities in body mass among college students: Understanding the role of early life adversity. *Journal of Behavioral Medicine*, *39*, 866–875. doi: 10.1007/s10865-016-9756-4

Curtis, D. S., Fuller-Rowell, T. E., Hinnant, J. B., Kaeppler, A. K., & Doan, S. N. (2017). Resting high-frequency heart rate variability moderates the association between early life adversity and body adiposity. *Journal of Health Psychology*, 1–11. doi: 10.1177/1359105317739964

Dabas, A., & Seth, A. (2018). Prevention and Management of childhood obesity. *Indian Journal of Pediatrics*, *85*, 546–553. doi: 10.1007/s12098-018-2636-x

Dallaker, M., & Hertwig, R. (2019). Quality matters: A meta-analysis on components of healthy family meals. *Health Psychology*, *38*, 1137–1149. doi:10.1037/hea0000801

Dev, D. A., McBride, B. A., Fiese, B. H., Jones, B. L., & Cho, H. (2013). Risk factors for overweight/obesity in preschool children: An ecological approach. *Childhood Obesity, 9*, 399–408. doi:10.1089/chi.2012.0150

Dinkel, D., Tibbits, M., Hanigan, E., Nielsen, K., Jorgensen, L., & Grant, K. (2017). Healthy families: A family-based community intervention to address childhood obesity. *Journal of Community Health Nursing*, *34*, 190–202. doi: 0.1080/07370016.2017.1369808

Dube, N., Khan, K., Loehr, S., Chu, Y., & Veugelers, P. (2017). The use of entertainment and communication technologies before sleep could affect sleep and weight status: A population-based study among children. *International Journal of Behavioral Nutrition and Physical Activity*, *14*, 97. doi: 10.1186/s12966-017-0547-2

Dwyer, L. Oh, A., Patrick, H. & Hennessy, E. (2015). Promoting family meals: A review of existing interventions and opportunities for future research. *Adolescent Health, Medicine and Therapeutics*, *6*, 115131. doi:10.2147/AHMT.S37316

Edberg, M. (2020). *Essentials of health behavior: Social and behavioral theory in public health* (3rd ed.). Burlington, MA: Jones & Bartlett Learning.

Elmore, S. & Sharma, M. (2014). Predicting childhood obesity prevention using social cognitive theory among upper elementary African-American children. *International Quarterly of Community Health Education*, *34*, 187–197. doi:10.2190/IQ.34.f

Fatima, Y., Doi, S. A. R., & Mamun, A. A. (2015). Longitudinal impact of sleep on overweight and obesity in children and adolescents: A systematic review and bias-adjusted meta-analysis. *Obesity Reviews, 16*, 137–149. doi:10.111/obr.12245

Fiese, B. H., & Bost, K. K. (2016). Families ecologies and child risk of obesity: Focus on regulatory processes. *Family Relations*, *65*, 94–107. doi:10.1111/fare.12170

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*, 1338–1342. doi:10.1073/pnas.1321355110

Fulkerson, J. A., Larson, N., Horning, M., & Neumark-Sztainer, D. (2014). A review of associations between family or shared meal frequency and dietary weight status outcomes across the lifespan. *Journal of Nutrition Education and Behavior, 46*, 2–19. doi: 10.1016/j.neb.2013.07.012

Fulkerson, J. A., Friend, S., Flattum, C., Horning, M., Draxten, M., Neumark-Sztainer, D., …Kubik, M. Y. (2015). Promoting healthful family meals to prevent obesity: HOME Plus, a randomized controlled trial. *International Journal of Behavioral Nutrition and Physical Activity*, *12*, 1–12. doi:10.1186/s12966-015-0320-3

Gohil, A., & Hannon, T. S. (2018). Poor sleep and obesity: Concurrent epidemics in adolescent youth. *Frontiers in Endocrinology, 9*, 1–8. doi: 10.3389/fendo.2018.00364

Gordon, N. P., & Mellor, R. G. (2015). Accuracy of parent-reported information for estimating prevalence of overweight and obesity in a race-ethnically diverse pediatric clinic aged 3 to 12. *BMC Pediatrics*, *15*, 1–11. doi: 10.1186/s12887-015-0320-0

Greer, A. E., Davis, S., Sandolo, C., Gaudet, N., & Castrogivanni, B. (2018). Formative research to create a farm-to-school program for high school students in a lower income, diverse, urban community. *Journal of School Health*, *88*(6), 453–461. doi: 10.1111/josh.12627

Grossman, D. C., Bibbins-Domingo, D. C., Curry, K., Barry, S. J., Davidson, M. J., Doubeni, K. W., … Tseng, A. (2017). Screening for obesity in children and adolescents U.S. preventive services task force recommendation statement. *Journal of the American Medical Association*, *317*, 2417–2426. doi: 10.1001/jama.2017.6803

Gunther, C., Rogers, C, Holloman, C., Hopkins, L. C., Anderson, S. E., Miller, C. K., …Penicka, C. (2019). Child diet and health outcomes of the simple suppers program: A 10-week, 2-group quasi-experimental family meals trials. *BMC Public Health*, *19*, 1657. doi:10.1186/s12889-019-7930-7

Hammersley, M. L., Jones, R. A., & Okely, A. D. (2017). Time2bhealthy - An online childhood obesity prevention program for preschool-aged children: A randomized controlled trial protocol. *Contemporary Clinical Trials*, *61*, 73–79. doi:10.1016/j.cct.2017.07.022

Hart, C. N., Hawley, N., Davey, A., Carskadon, M., Raynor, H., Jelalian, E., … Wing, R. R. (2017). Effect of experimental change in children’s sleep duration on television viewing and physical activity. *Pediatric Obesity*, *12*, 462–467. doi:10.111/ijpo.12166

Harvard T. H. Chan School of Public Health. (2018a). *Child obesity: Too many kids are too heavy, too young.* Retrieved from https://www.hsph.harvard.edu/obesity-prevention-source/obesity-trends/global-obesity-trends-in-children/

Harvard T. H. Chan School of Public Health. (2018b). *The Nutrition Source: Measuring physical activity.* Retrieved from https://www.hsph.harvard.edu/nutritionsource/mets-activity-table/

Herman, K. M., Chaput, J., Sabiston, C. M., Matthieu, M., Tremblay, A., & Paradis, G. (2015). Combined physical activity/sedentary behavior associations with indices of adiposity in 8- to -10-year-old children. (2015). *Journal of Physical Activity and Health*, *12,* 20–29. doi:101123/jpah.2013-0019

Hoyt, L. T., Kushi, L., Leung, C. W., Nickleach, D. C., Adler, N., Laraia, B. A., Hiatt, R. A., & Yen, I. H. (2014). Neighborhood influences on girls' obesity risk across the transition to adolescence. *Pediatrics, 134*(5), 942–949. doi:10.1542/peds.2014-128

Hulst, A. V., Roy-Gagnon, M., Gauvin, L., Kestens, Y., Henderson, M., & Barnett, T. A. (2015). Identifying risk profiles for childhood obesity using recursive partitioning based on individual, familial, and neighborhood environment factors. *International Journal of Behavioral Nutrition and Physical Activity*, *12*, 1–9. doi:10.1186/s12966-015-0175-7

Jernigan, J., Khan, L. K., Dooyema, C., Ottley, P., Harris, C., Dawkins-Lyn, N., . . . Young-Hyman, D. (2018). Childhood obesity declines project: Highlights of community strategies and policies. *Childhood Obesity, 14,* S32–S39. doi: 10.1089/chi.2018.0022

Jones, B. L. (2018). Making time for family meals: parental influences, home eating environments, barriers and protective factors. *Physiology & Behavior*, *193*, 248–251. doi: 10.1016/j.physbeh.2018.03.035

Jordan, N., Graham, A. K., Berkel, C., & Smith, J. D. (2019). Costs of preparing to implement a family-based intervention to prevent pediatric obesity in primary care: A budget impact analysis. *Prevention Science*, *20*, 655–664. doi:10.1007/s11121-018-0970-x

Kakinami, L., Barnett, T. A, Séguin, L., & Paradis, G. (2015). Parenting styles and obesity risk in children. *Preventive Medicine*, *75*, 18–22. doi:10.1016/j.ypmed.2015.03.005

Kellous, N., Sandalinas, F., Copin, N., & Simon, C. (2014). Prevention of unhealthy weight in children by promoting physical activity using a socioecological approach: What can we learn from intervention studies? *Diabetes and Metabolism*, *40*, 258–271. doi: 10.1016/j.diabet.2014.01.002

Klingenberg, L., Chaput, J-P., Holmbäck, U., Jennum, P., Astrup, A., & Sjödin, A. (2012). Sleep restriction is not associated with a positive energy balance in adolescent boys. *The American Journal of Clinical Nutrition*, *96*(2), 240–248

Knowlden, A. P., & Conrad, E. (2018). Two-year outcomes of the enabling mothers to prevent pediatric obesity through web-based education and reciprocal determinism (EMPOWER) randomized control trial. *Health Education & Behavior*, *45*, 262–276. doi:10.1177/1090198117732604

Knowlden, A. P., & Sharma, M. (2015). Social cognitive maternal-mediated nutritional correlates of childhood obesity. *Applied Research and Evaluation*, *35*, 177–191. doi:10.1177/0272684X15569678

Koning, M., Jong, A., D., Jong, E. D., Visscher, T. L. S., Seidell, J. C., & Renders, C. M. (2018). Agreement between parent and child report of physical activity, sedentary and dietary behaviours in 9-12-year-old children and associations with weight status. *BMC Psychology*, *6*, 1–11. doi: 10.1186/s40359-018-0227-2

Kyle, T., Stanford, F., & Nadglowski, J. (2018). Addressing Weight Stigma and Opening Doors for a Patient-Centered Approach to Childhood Obesity. *Obesity.*, *26*, 457–458. doi:10.1002/oby.22084

Krietsch, K. N., Chardon, M. L., Beebe, D. W., & Janicke, D. M. (2019). Sleep and weight-related factors in youth: A systematic review of recent studies. *Sleep Medicine Reviews*, *46*, 87–96. doi:10.1016/j.smrv.2019.04.010

Larson, N., Wang, Q., Berge, J. M., Shanafelt, A., & Nanney, M., S. (2016). Eating breakfast together as a family: Mealtime experience and associations with dietary intake among adolescents in rural Minnesota, USA. *Public Health Nutrition*, *19*, 1565–74. doi: 10.1017/S1368980016000379

LeBourgeois, M. K., Hale, L., Chang, A. M., Akacem, L. D., Montgomery-Downs, H. E., & Buxton, O. M. (2017). Digital media and sleep in childhood and adolescence. *Pediatrics*, *140*, S92–S96. doi:10.1542/peds.2016-1758J

Lee, J., Kubik, M. Y., & Fulkerson, J. A. (2018). Media devices in parents' and children's bedrooms and children's media use. *American Journal of Health Behavior*, *42,* 135–143. doi:10.5993/AJHB.42.1.13

Lee, H. J., Lee, S. Y., & Park, E. C. (2016). Do family meals affect childhood overweight or obesity?: Nationwide survey 2008–2012. *Pediatric Obesity*, *11*, 161–165. doi:10.1111/ijpo.12035

Lewin, D. S., Wolfson, A. R., Bixler, E. O., & Carskadon, M. A. (2016). Duration isn't everything. Healthy sleep in children and teens: Duration, individual need and timing. *Journal of Clinical Sleep Medicine*, *12,* 1549–1561. doi: 10.5664/jcsm.6260

Liu, W., Liu, W., Lin, R., Li, B., Pallan, M., Cheng, K. K., & Adab, P. (2016). Socioeconomic determinants of childhood obesity among primary school children in Guanzhou, China. *Biomedical Central Public Health*, *16*, 1–8. doi:10.1186/s12889-016-3171-1

Long, M. W.,Ward, Z. J., Resch, S. C., Cradock, A. L., Wang, Y. C., Giles, C. M., & Gortmaker, S. L. (2016). State-level estimates of childhood obesity prevalence in the United States corrected for report bias. *International Journal of Obesity*, *40,* 1523–1528. doi:10.1038/ijo.2016.130

Loth, K. A., Uy, M. J. A., Winkler, M. R., Neumark-Sztainer, D., Fisher, J. O., & Berge, J. M. (2018). The intergenerational transmission of family meal practices: A mixed-methods study of parents of young children. *Public Health Nutrition*, *1*, 1–12. doi:10.1017/S1368980018003920

McGee, B. B., Richardson, V., Johnson, G., & Johnson, C. (2017). Perceptions of food intake, physical activity, and obesity among African-American children in the lower Mississippi Delta. *American Journal of Health Promotion*, *31*, 333–335. doi:10.4278/ajhp.130611-ARB-296

McGeown, L., & Davis, R. (2017). Social modeling of eating mediated by mirror neuron activity: A causal model moderated by frontal asymmetry and BMI. *Behavioural Brain Research*, *338*, 66–75. doi:10.1016/j.bbr.2017.10.009

Narcisse, M-R., Long, C. R., Felix, H. C., Howie, E. K., Purvis, R. S., & McElfish, P. A. (2019). Adherence to sleep guidelines reduces risk of overweight/obesity in addition to 8-5-2-1-0 guidelines among a large sample of adolescents in the United States. *Sleep Health*, *5*, 444–451. doi:101016/j.sleh.2019.03.004

National Institute of Health. (2016). *How are obesity & overweight diagnosed?* Retrieved from https://www.nichd.nih.gov/health/topics/obesity/conditioninfo/diagnosed

National Library of Medicine. (n.d.a). *Obesity*. Retrieved from https://www.ncbi.nlm.nih.gov/mesh?Db=mesh&Term=%22Obesity%20%22 [MESH]

National Library of Medicine. (n.d.b). *Overweight*. Retrieved from https://www.ncbi.nlm.nih.gov/mesh/?term=overweight

National Library of Medicine. (n.d.c). *Family*. Retrieved from https://www.ncbi.nlm.nih.gov/mesh/68005190

National Library of Medicine. (n.d.d). *Sleep*. Retrieved from https://www.ncbi.nlm.nih.gov/mesh/68012890

National Library of Medicine. (n.d.e). *Risk factors*. Retrieved from https://www.ncbi.nlm.nih.gov/mesh/?term=Risk+Factors

National Sleep Foundation. (2018a). *How much sleep do we really need?* Retrieved from https://sleepfoundation.org/how-sleep-works/how-much-sleep-do-we-really-need

National Sleep Foundation. (2018b). *A good night's sleep can help you maintain a healthy weight.* Retrieved from https://sleepfoundation.org/sleep-news/good-nights-sleep-can-help-you-maintain-healthy-weight

Nguyen, B. T., Shuval, K., Bertmann, F., & Yaroch, A. L. (2015). The supplemental nutrition assistance program, food insecurity, dietary quality, and obesity among U.S. adults. *American Journal of Public Health*, *105*, 1453–1459. doi: 10.2105/AJPH.2015.302580

Obesity Action Coalition. (2018). *What is childhood obesity?* Retrieved from https://www.obesityaction.org/get-educated/understanding-childhood-obesity/what-is-childhood-obesity/

Odgers, C. (2018). Smartphones are bad for some teens, not all. *Nature*, *554*, 432–438. Retrieved from http://www.nature.com.ezp.twu.edu/magazine-assets/d41586-018-02109-8/d41586-018-02109-8.pdf

Office of Disease Prevention and Health Promotion. (2018). *Everyone has a role in supporting healthy eating patterns: The social-ecological model.* Retrieved from https://health.gov/dietaryguidelines/2015/guidelines/chapter-3/social-ecological-model/

Ogden, C. L., Carroll, M. D., Lawman, H. G., Fryar, C. D., Kruszon-Moran, D., Kit, B. K., & Flegal, K. M. (2016). Trends in obesity prevalence among children and adolescents in the United States, 1988–1994 through 2013–2014. *Journal of the American Medical Association*, *315*, 2292–2299. doi: 10.1001/jama.2016.6361

Ogilvie, R. P., & Patel, S. R. (2017). The epidemiology of sleep and obesity. *Sleep Health*, *3*, 383–388. doi:10.1016/j.sleh.2017.07.013

Oklahoma State Department of Health. (2019a). *Oklahoma vs. U.S. 2013 YRBS*. Retrieved from https://www.ok.gov/health2/documents/ok_comp_US_2013.pdf

Oklahoma State Department of Health. (2019b). *Obesity fact sheet: YRBS 2017*. Retrieved from https://www.ok.gov/health2/documents/YRBS_2017_Obesity_Fact_Sheet.pdf

Oklahoma State Department of Health. (2019c). *Fifth grade health survey.* Retrieved from https://www.ok.gov/health/Family_Health/Maternal_and_Child_Health_Service/Data_and_Evaluation/Fifth_Grade_Health_Survey/Fifth_Grade_Health_Survey_Results/

Oklahoma State Department of Health. (2019d). *Obesity infographic: YRBS 2017*. Retrieved from https://www.ok.gov/health2/documents/17191MCHS%20-%20YRBS%20Obesity%20Infographic%202017_final.pdf

Olson, J., Aldrich, H., Callahan, T. J., Matthews, E. E., & Gance-Cleveland, B. (2015). Characterization of childhood obesity and behavioral factors. *Journal of Pediatric Health Care*, *30*, 444–452. doi:10.1016/j.pedhc.2015.10.009

Ortega, F. B., Sui, X., Lavie, C. J., & Blair, S. N., (2016). Body mass index, the most widely used but also criticized index: Would a criterion measure of total body fat be a better predictor of cardiovascular disease mortality? *Mayo Clinic Proceedings*, *91*,443–455. doi: 10.1016/j.mayocp.2016.01.008

Paruthi, S., Brooks, L. J., D'Ambrosio, C., Hall, W. A., Kotagal, S., Lloyd, R. M, … Wise, M. S. (2016). Recommended amount of sleep for pediatric populations: A consensus statement of the American Academy of Sleep Medicine. *Journal of Sleep Medicine*, *12*, 785–786. doi:10.5664/jcsm.5866

Pratt, C. A., Loria, C. M., Artaega, S. S., Nicastro, H. L., Lopez-Class, M., Jesus, J. D., … Gavini, N. (2017). A systematic review of obesity disparities research. *American Journal of Preventive Medicine*, *53*, 113–122. doi:10.1016/j.amepre.2017.01.041

Reid Chassiakos, Y. L., Radesky, J., Christakis, D., Moreno, M. A. & Cross, C. (2016). Children and adolescents and digital media. *Pediatrics*, *138*, e1–e18. doi: 10.1542/peds.2016-2593

Rendall, M. S., Weden, M. M., Lau, C. Brownell, P., Nazarov, Z., & Fernandes, M. (2014). From evaluation bias in estimates of early childhood obesity from parent-reported heights and weights. *American Journal of Public Health, 104*, 1255–1262. doi: 10.2105/AJPH.2014.302001

Reutrakul, S., & Cauter, E. V. (2018). Sleep influences on obesity, insulin resistance, and risk of type 2 diabetes. *Metabolism, 84*, 56–66. doi:10.1016/j.metabl.2018.02.010

Rimer, B., K. & Glanz, K. (2005). *Theory at glance: A guide for health promotion practice* (2nd ed.). Bethesda, MD: U.S. Department of Health and Human Services, National Institute of Health, & National Cancer Institute.

Robinson, T. N., Banda, J. A., Hale, L, Lu, A. S., Fleming-Milici, F., Calvert, S., & Wartella, E. (2017). Screen media exposure and obesity in children and adolescents. *Pediatrics, 140*, S97–S101. doi: 10.1542/peds.2016-1758K

Rogers, C., Anderson, S. E., Dollahite, J. S., Hill, T. F., Holloman, C., Miller, C. K., …, & Gunther, C. (2017). Methods and design of a 10-week multi-component family meals intervention: A two group quasi experimental effectiveness trial. *BMC Public Health, 17*, 1471–2458. doi: 10.1186/s12889-016-3908-x

Ross, S. E., Flynn, J. I., & Pate, R. R. (2016). What is really causing the obesity epidemic? A review of reviews in children and adults. *Journal of Sports Sciences, 34*, 1148–1153. doi:10.1080/02640414.2015.1093650

Sagar, R., & Gupta, T. (2018). Psychological aspects of obesity in children and adolescents. *Indian Journal of Pediatrics, 85*, 554–559. doi:10.1007/s12098-017-2539-2

Sahoo, K., Sahoo, B., Choudhury, A. K., Sufi, N. Y., Kumar, R., & Bhadoria, A. S. (2015). Childhood obesity: Causes and consequences. *Journal of Family Medicine & Primary Care, 4*(2), 187–192. doi:10.4103/2249-4863.154628

Sallis, J. F., Owen, N., & Fisher, E. B. (2008). Ecological models of health behavior. In Glanz, K., Rimer, B. K., & Viswanath, K. (Eds.), *Health behavior and health education: Theory, research, and practice* (4th ed., pp. 465–482). San Francisco, CA: John Wiley & Sons.

Schuler, B. R., & O'Reilly, N. (2017). Child development and the community environment: Understanding overweight across the income gradient. *Childhood Obesity*, *13*, 479–489. doi:10.1089/chi.2017.0025

Shape Your Future. (2018). *Overweight and obesity's impact on Oklahoma.* Retrieved from https://shapeyourfutureok.com/overweight-obesitys-impact-oklahoma/

Sharma, M. (2017). *Theoretical foundations of health education and health promotion,* (3rd ed.). Burlington, MA: Jones & Bartlett Learning.

Tanskey, L., Goldberg, J., Chui, K., Must, A., & Sacheck, J. (2018). The state of the summer: A review of child summer weight gain and efforts to prevent it. *Current Obesity Reports*, *7*, 112–121. doi: 10.1007/s13679-018-0305-z

The State of Obesity. (2018a). *The state of childhood obesity.* Retrieved from https://stateofobesity.org/childhood-obesity-trends/

The State of Obesity. (2018b). *The state of obesity in Oklahoma.* Retrieved from https://stateofobesity.org/states/ok

The State of Obesity. (2019). *Obesity rates, children ages 10 to 17.* Retrieved from https://stateofchildhoodobesity.org/children1017/

U.S. Census Bureau. (2017). *2016 National survey of children's health: Frequently asked questions.* Retrieved from https://census.gov/content/dam/Census/programs-surveys/nsch/tech-documentation/methodology/NSCH-2016-FAQs.pdf

U.S. Census Bureau. (2018). *2016 National survey of children's health: Methodology report.* Retrieved from https://census.gov/content/dam/Census/programs-surveys/nsch/tech-documentation/methodology/2016-NSCH-Methodology-Report.pdf

Urlacher, S. S., Snodgrass, J. J., Dugas, L. R., Sugiyama, L. S., Liebert, M. A., Joyce, C. J., & Pontzer, H. (2019). Constraints and trade-offs regulate energy expenditure during childhood. *Science Advances, 5,* 1–8. doi:10.1126/sciadv.aax1065

Valdés, J., Rodríguez-Artalejo, Aguillar, L., Jaén-Casquero, M. B., & Royo-Bordonada, M. Á. (2013). Frequency of family meals and childhood overweight: a systematic review. *Pediatric Obesity, 8*, e1–e13. doi: 10.1111/j.2047-6310.2012.00104.x

Vaughn, A. E., Ward, D. S., Fisher, J. O., Faith, M., Hughes, S. O., Kremers, S. P. J., …, Power, T. J. (2016). Fundamental constructs in food parenting practices: A content map to guide future research. *Nutrition Reviews*, *74*, 98–117. doi:10.1093/nutrit/nuv061

Von Hipel, P. T., & Nahhas, R. W. (2013). Extending the history of childhood obesity in the United States: The fels longitudinal study, birth years 1930-1993. *Obesity, 21,* 2153–2156. doi:10.1002/oby.20395

Von Hipel, P. T., Nahhas, R. W., & Czerwinski, S. A. (2015). How much do children's body mass indices changeover intervals of 6–12 months? Statistics from before and during the obesity epidemic. *Pediatric Obesity, 10*, 468–475. doi:10.1111/ijpo.12008

Weaver, S. P., Kelley, L., Griggs, J., Weems, S., & Meyer, M. R. (2014). Fit and healthy family camp for engaging families in a child obesity intervention. *Family & Community Health, 37*, 31–34. doi:10.1097/FCH.0000000000000012

Widome, R., Lenk, K. M., Laska, M. N., Erickson, D. J., Iber, C., Kilian, G., & Wahlstrom, K. (2019). Sleep duration and weight-related behaviors among adolescents. *Childhood Obesity, 15,* 434–442. doi:10.1089/chi.2018.0362

Wilson, D. K., Sweeney, A. M., Kitzman-Ulrich, H., Gause, H., & St. George, S. M. (2017). Promoting social nurturance and positive social environments to reduce obesity in high-risk youth. *Clinical Child and Family Psychology Review, 20,* 64–77. doi:10.1007/s10567-017-0230-9

Wright, D. R., Glanz, K., Colburn, T., Robson, S. M., & Saelens, B. E. (2018). The accuracy of parent-reported height and weight for 6-12-year-old U.S. children. *BMC Pediatrics, 18,* 1–8. doi:10.1186/s12887-018-1042-x

Yavuz, H. M., & Selcuk, B. (2018). Predictors of obesity and overweight in preschoolers: The role of parenting styles and feeding practices. *Appetite, 120*, 491–499. doi:10.1016/j.appet.2017.10.001

Zoellner, J. M., Hill, J., You, W., Brock, D., Frisard, M., Alexander, R., … Estabrooks, P. A. (2017). The influence of parental health literacy status on reach, attendance, retention, and outcomes in a family-based childhood obesity treatment program, Virginia, 2013-2015. *Preventing Chronic Disease*, *14*, 1–11. doi:10.5888/pcd14.160421