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School Lunch Timing and Student Body Mass Index

Megan Monteith
Walden University

Walden University

College of Health Sciences and Public Policy

This is to certify that the doctoral study by

Megan D. Monteith

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

Review Committee
Dr. Peter Anderson, Committee Chairperson, Public Health Faculty
Dr. Jennifer Gadarowski, Committee Member, Public Health Faculty
Dr. Tolulope Osoba, University Reviewer, Public Health Faculty

Chief Academic Officer and Provost
Sue Subocz, Ph.D.

Walden University
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Abstract

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MPH, University of Oklahoma Health Sciences Center, 2010

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Doctoral Study Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Public Health

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Abstract

Obesity continues to be a leading public health issue in the United States. Many chronic diseases are associated with obesity, including hypertension, diabetes, and several forms of cancer. There are multiple known contributing factors to obesity; however, historically, there has been little research focusing on time of day eating as a possible risk factor for obesity, especially childhood obesity. Childhood obesity is a significant risk factor for adult obesity. Obese children and adolescents are five times more likely to be obese in adulthood. The theoretical foundation for this study was the social ecological model. In this secondary correlational analysis using the 2004-2005 School Nutrition Dietary Assessment data set, the association between mealtime and body mass index was examined using descriptive statistics, and logistic regression analysis. The population for this study included all respondents who participated in the 2004-2005 SNDA-III (N = 2,314). The focus of this study was school mealtimes and childhood obesity, potentially identifying another contributing factor to the obesity epidemic in the United States. The results of this study indicated that there was not enough evidence to suggest an association between school mealtimes and childhood obesity; however, there was the potential for further research on school mealtimes and the school environment. These findings build upon the body of knowledge and may be used by school policy makers, school administration, and parents to promote more appropriate lunch mealtimes and other measures, which can lead to positive social change.

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Dedication

This doctoral study is dedicated to my family. My husband, Mark Monteith, for supporting me, cheering me onward, and loving me. Thank you for always believing in me, even when I did not believe in myself. My children, Maelyn and Marston, thank you for being so patient when Mommy had “school to do.” Please know that you are capable of absolutely anything if you have passion, persistence, and patience. My parents and in-laws, thank you for always being willing to keep the children at your house so that I could work in peace and quiet. This would not have been possible without you all!

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To my friend and classmate Ciara Martin Fox, thank you for being by my side through all of this. Knowing you were just a text away, to cry and laugh with, made the hard times good and the good times great!

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Section 1: Foundation of the Study and Literature Review

Introduction

Obesity continues to rise across the United States, putting a strain on overall health, health care costs, productivity, and military readiness (Centers for Disease Control and Prevention [CDC], 2021a). Childhood obesity is also a severe problem in the United States. While more than 1 in 3 adults struggles with obesity, about 1 in 5 children also struggle with obesity. Children with obesity are more likely to have obesity as adults (CDC, 2021a). Nutrition and physical activity are well known for contributing to weight gain; however, when people eat may also be a factor that contributes to obesity (Bandin et al., 2015; Bo et al., 2015; Garaulet & Gómez-Abellán, 2014; Gill & Panda, 2015; Goheer et al., 2021; St-Onge et al., 2017). However, the researchers did not explore or consider meal timing for children in these studies.

This gap in the literature presented an opportunity to assess and understand differences in body mass index (BMI) among school-aged children when comparing the time of day lunch is eaten. Therefore, conducting a comprehensive cross-sectional quantitative study that included the lunch timing of students as a variable associated with obesity could provide more relevant information about factors that may influence this population. This approach strengthens existing studies pertinent to this topic while spanning the gap in the literature. Conducting a thorough, in-depth analysis of school lunchtimes in relation to student BMI has the potential to equip parents, school administrators, and policymakers to make better-informed decisions when creating or modifying policies around when lunch is served.

In the following sections of this section, I discuss the background and rationale for this study, the problem statement, the purpose of the study, the research questions, the theoretical framework, and the nature of the study. This section also provides a comprehensive literature review and concludes with the significance of the study.

Background

Childhood obesity has reached an epidemic level in the United States. There is no single cause of childhood obesity; it is a multifaceted issue. While the Latin term *adiposity* has a more encompassing meaning than the English term *obesity*, meaning both excess fat mass and the fat in fatty tissue, the term used throughout this paper is obesity (see Zou et al., 2019). Childhood obesity is a significant predictor of adulthood obesity (Llewellyn et al., 2016). Obese children are more likely to suffer chronic health conditions later in life, including cancer, stroke, Type 2 diabetes, high blood pressure, joint problems, gallstones, and other diseases (Kahan & McKenzie, 2015; National Institutes of Health [NIH], 2017). In the United States, the prevalence of childhood obesity was 19.3% in 2017-2018 (CDC, 2019). About 14.4 million children and adolescents are obese, with almost 1 in 5 U.S. children falling into this category.

Energy imbalances influence overweightness and obesity in the body. This happens when the body consumes more calories than it burns. The most common factors contributing to weight gain include genetics, eating habits, physical inactivity, T.V., computer, phone, other screen time, sleep habits, medical conditions or medications, access to healthy foods, and safe places to be active (NIH, 2017). While it may be difficult to tell if a child is overweight, as children grow at different rates at different times, a BMI growth chart compares a child's BMI with other children of the same sex and age (NIH, 2017). Childhood obesity is defined as "a body mass index (BMI) at or above the 95th percentile of the CDC sex-specific BMI-for-age-growth charts" (CDC, 2019).

School influences children's lives significantly, affecting their external synchronizers of the biological clock. These synchronizers include changes from fasting to eating, resting to activity, light exposure, and sleep duration (Barraco et al., 2019). These body clock synchronizers affect the circadian system function, and disruption or inadequate exposure may contribute to the risk of developing metabolic diseases. do Amaral e Melo et al. (2020) suggested that meals should be at regular times and not hurried. Meals should also be eaten in appropriate locations and together with family and friends whenever possible. Children do not control when they eat, how long the mealtime is, or who they get to eat with at school. These disruptions may have an impact on obesity for school-going children.

This study was focused on the growing childhood obesity problem and how meal timing may affect this. Social changes are necessary to decrease childhood and ultimately adult obesity (Sanyaolu et al., 2019). Sanyaolu et al. (2019) also recognized that childhood obesity is a public health issue that can affect a person across the lifespan. Positive social change from this study could lead parents and schools to review, support, and implement policies to serve students' energy intake needs better. This can be accomplished by providing parents and school leaders with information to raise awareness of meal timing and how it affects their children and students. Due to the high childhood obesity rates in the United States, the results from this study could contribute to positive social change by reducing obesity among U.S. children.

Problem Statement

According to the CDC (2019), for children aged 2 to 19 years, the prevalence of obesity was 19.3% in 2018, affecting about 14.4 million children and adolescents. The National School Lunch Program dictates that students should be served lunch between 10 a.m. and 2 p.m., but this leaves unequal time gaps between meals for some students. For a student who eats breakfast at school at 8:30 a.m., a 10 a.m. lunchtime gives only an hour and a half between meals, with approximately 7 hours until a possible 5 p.m. dinner time. Chapman et al. (2017) showed that the time of day school meals are eaten contributes to what and how much a student eats but did not look at corresponding weights. Lopez-Minguez et al. (2019) discovered that the timing of meals plays a crucial role in obesity for adults, but not for children. In this study, I examined whether there is an association between school mealtimes and the likelihood of school children being obese. Although researchers have investigated this issue, there is a gap in the literature on the association between school mealtimes and childhood obesity.

Purpose of the Study

The purpose of this cross-sectional quantitative study was to examine the association between school mealtimes and childhood obesity among school-going children and whether there were significant differences when controlling for age, gender, race, and socioeconomic status. Research around meal timing and its relation to weight status has looked at the adult population, not children and adolescents. In fact, a review of the literature revealed the lack of comprehensive quantitative studies specifically focused on a student population (Garaulet et al., 2013; Goheer et al., 2021; Jakubowicz et al., 2013; Kahleova et al., 2017; Lopez-Minguez et al., 2019; St-Onge et al., 2017; Xiao et al., 2019). Given that childhood obesity increases the risk of obesity later in life and that obesity is a predictor for numerous chronic diseases, scholars must pay more attention to the factors contributing to childhood obesity.

The population group for this study consisted of American primary and secondary school students. School lunchtime was the independent or predictor variable for Research Question (RQ) 1, and how the student perceived the lunch timing for RQ2. BMI was the dependent variable for all RQs. The covariates were age, gender, race, and socioeconomic status.

Research Questions and Hypotheses

RQ1: Is there a significant association between the time school lunches are served and student BMI when controlling for age, gender, race, and socioeconomic status?

$H_0$1: There is no significant association between the time school lunches are served and student BMI when controlling for age, gender, race, and socioeconomic status.

H_A1: There is a significant association between the time school lunches are served and student BMI when controlling for age, gender, race, and socioeconomic status.

RQ2: Is there an association between perceived meal timing and student BMI controlling for age, gender, race, and socioeconomic status?

$H_0 2$: There is no association between perceived meal timing and student BMI when controlling for age, gender, race, and socioeconomic status.

$H_A 2$: There is an association between perceived meal timing and student BMI when controlling for age, gender, race, and socioeconomic status.

Theoretical Framework

The social-ecological model (SEM) is a theoretical framework created by Bronfenbrenner (1979). The SEM was incorporated into this study to examine whether there was an association between meal timing and childhood obesity. The SEM framework includes factors that may also play a role in influencing behavior by viewing this issue through the lens of the individual, interpersonal, organizational, community, and policy levels (Glanz et al., 2015). The SEM approach looks at how different methods can be integrated to change the physical and social environments rather than focusing solely on modifying individual health behaviors (CDC, 2015b).

The SEM was chosen as a framework for my study as childhood obesity has various factors that contribute to it. Stokols (1996) proposed several core principles that incorporate the SEM into community engagement. The principles guiding this study are as follows: (a) Individuals operate in multiple environments that overlap and influence each other, (b) there are environmental forces that influence health and well-being, (c) the same environment may affect individuals differently, and (d) physical, social, and cultural dimensions of an individual's environment influence health status. The SEM is explored more later in this section.

Nature of the Study

In this study, I used a quantitative cross-sectional research design to examine the association between meal timing and obesity among school-aged children in the United States. In a cross-sectional study design, measurements are taken at one point in time, are relatively inexpensive to operate, and can be completed in less time (Sedgwick, 2014). I used data from the 2004-2005 School Nutrition and Dietary Assessment (SNDA-III) for this study. The SNDA-III is the third iteration of the survey. The researchers collected 2,314 child/youth interview surveys from a nationally representative sample. The methodology is further explained in Section 2.

This study's independent variables were the time of lunch and perceived lunch timing. Weight and height, which were converted to BMI, was the dependent variable. Covariates included age, gender, race, and socioeconomic status. I examined the relationships between these variables in the hopes of effecting positive social change.

Literature Search Strategy

Childhood and adolescent obesity have and continue to be studied a great deal. However, gaps in the literature have suggested that more research is needed in how meals are associated with obesity among school-aged children in the United States (Bhatt, 2014; Chapman et al., 2017; Lopez-Minguez et al., 2019; Pandolfi et al., 2016). For this study, scholarly literature published from 2014 to 2021 was reviewed, emphasizing peer-reviewed literature. Literature was compiled from the following databases accessed through the Walden University Library: Academic Search Complete, Medline, ProQuest, Pubmed, and Thoreau. Additionally, searches through Google Scholar and the CDC were also reviewed. The search strategy included the following keywords: *school mealtimes, school meal times, school meal timing, recess before lunch, eating time, childhood obesity, lunch and recess times, meals, food, breakfast, lunch, school, education, classroom, weight, obesity, overweight, body mass index, BMI, eating behavior, eating habits, energy intake,* and *food intake*. The terms and phrases were entered individually and in different forms to obtain related articles for this literature review.

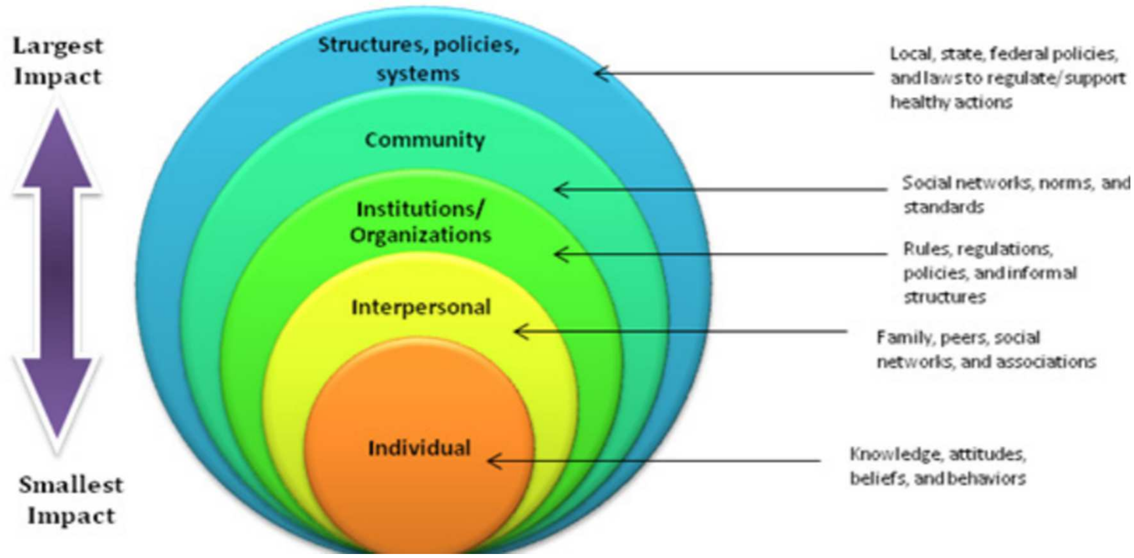
Theoretical Foundation of the Study

The theory and framework used to guide this study was Bronfenbrenner's (1977) ecological framework for human development, or the SEM. The SEM illuminates environmental factors and helps show the dynamic between individuals and their environment (Larson et al., 2016).

The SEM was adapted from Bronfenbrenner's ecological systems theory and has been widely adapted for public health research. Bronfenbrenner's framework, introduced in 1979, looks at the multifaceted connections between individuals and their environments on multiple levels. These numerous levels influence health behavior (Bronfenbrenner, 1979). The SEM levels include intrapersonal, interpersonal, organizational, community, and public policy (Glanz et al., 2015, p. 48). Jernigan et al. (2018) discovered that using an SEM framework to study programs and policies at different levels can provide important information about successful interventions to improve obesity outcomes. Figure 1 shows an illustration of the SEM.

Figure 1

The Social-Ecological Model



Note. From *Health Equity Resource Toolkit: Disseminating guidance for state practitioners to address obesity disparities,* by the CDC, 2015a. https://www.cdc.gov/obesity/downloads/cdchealthequityobesitytoolkit508.pdf

Following the SEM, individual level factors include biological factors, such as age, sex, genetics, knowledge, attitudes, beliefs, and behaviors (CDC, 2021b). The interpersonal level has family, peers, and relationships. Rules, regulations, and policies are factors that contribute to the organizational level. The community level includes social networks and norms. The last level involves structures, policies, and systems with local, state, and federal laws and policies.

The SEM levels I have operationalized in this research study were the individual, interpersonal, organizational, structures, and policies; systems were not tested in this study. The individual level measures operationalized included demographic variables (age, sex, race,) and BMI. Socioeconomic status fits the interpersonal level. The meal timing at schools were measures at the organizational level. The structures, policies, and systems included state and federal-level policies regarding meal timing. To decrease childhood obesity, interventions should be designed with influences across all five SEM themes.

Literature Review Related to Key Variables and/or Concepts

The literature review for this study focused on childhood obesity, the prevalence of obesity in school-aged children in the United States, and the impact of meal timing on childhood obesity. I also examined the literature on variables that influence childhood obesity related to school meal timing lengths and timing of food consumption on academic performance.

Childhood and Adolescent Obesity

Prevalence

The prevalence of childhood obesity in the United States is high, reaching epidemic proportions. Childhood obesity is defined as “a body mass index (BMI) at or above the 95th percentile of the CDC sex-specific BMI-for-age-growth charts” (CDC, 2019, para. 3). According to the Trust for America’s Health (2020), obesity rates for children ages 2 to 19 more than tripled from 1976 to 2018. For those aged 2 to 19 years, the prevalence of obesity was 19.3% in 2017-2018, affecting about 14.4 million children and adolescents. The incidence can be further broken down by age from the 2015-2016 National Health and Nutrition Examination Survey (NHANES)—with 2 to 5 year-olds at 13.4%, 6 to 11 year-olds at 20.3%, and 12 to 19 year-olds at 21.2%—with the prevalence increasing by age (as cited in CDC, 2019). However, Anderson et al. (2019) discovered that obesity prevalence steadily increased at the cohort level until 10 years old. After the age of 10, the prevalence of obesity did not change. Obesity data on high school students from the 2019 Youth Risk Behavior Survey showed that 15.5% of students in Grades 9 to 12 were classified as obese, and 16.1% were overweight. This is a considerable increase from the survey results from 1999 that indicated a high school obesity rate of 10.6%. Childhood obesity had lingering consequences into adolescence, as seen by the increase in high school students' obesity rate.

Childhood obesity is even more widespread among specific populations. For example, Hispanics and non-Hispanic Blacks have a higher obesity prevalence than non-Hispanic Whites, with non-Hispanic Asians with the lowest obesity prevalence (CDC, 2019). From the 2017-2018 National Survey of Children's Health, Mississippi, West Virginia, Kentucky, and Louisiana had the highest obesity rates for children ages 10 to 17, while Utah, Minnesota, and Alaska had the lowest rates of childhood obesity. Despite their state of residence, boys are also more likely to be obese than girls (Trust for America's Health, 2020). Ethnicity, race, gender, and geographic location play a role in the prevalence of childhood obesity in the United States.

Rates of childhood obesity are higher in children from lower socioeconomic backgrounds. Hemmingsson (2018) argued that a low socioeconomic status is one of the strongest risk factors for developing obesity. Williams et al. (2018) discovered that children in the lowest quintile of socioeconomic status were 70% more likely to be obese or overweight than those in the highest quintile. Financial hardship can be a consequence of low socioeconomic status, which in turn makes healthy lifestyles less accessible (Hemmingsson, 2018). Socioeconomic status is yet another variable to consider in the childhood obesity dilemma.

Although there is no denying that childhood obesity is on the rise, the rapid increase has slowed in recent years, according to the 2015-2016 NHANES. The Supplemental Nutrition Program for Women, Infants, and Children (WIC) and the Healthy, Hunger-Free Kids Act (HHFKA) are two programs that have contributed to this decline (Anderson et al., 2019; Dietz, 2021). Both programs are aimed at reducing food insecurity for the most vulnerable populations. The WIC package revision in 2009 included more fruits, vegetables, whole grains, and lower-fat milk, substantially improving the quality of the foods provided and improving the children's diet quality in the program (Dietz, 2021; Tester et al., 2016). The HHFKA set standards for school meals for age-appropriate caloric ranges and requirements for plate composition according to food groups. Dietz (2021) discovered that these changes have led to an increase in school meal quality and improved consumption of school meals, increasing Health Eating Index 2010 scores by school lunch participants from 42.7 to 54.6. Together, WIC and HHFKA have reduced the prevalence of obesity and improved diets.

Causes

Childhood obesity cannot be confined to a single cause. Sanyaolu et al. (2019, para. 9) described obesity as a “chronic, multifactorial” disease commonly caused by excessive food intake and low energy expenditure. Genetic, psychological, lifestyle, nutritional, environmental, and hormonal factors are all possible contributors to obesity (Sanyaolu et al., 2019). Individuals can be susceptible to an elevated body fat mass by their genetics, including various factors associated with hypothalamic neurons. Neurohormonal control is responsible for energy regulation and can be impaired by genetic and environmental modulators. Sanyaolu et al. further explained that environmental modulators include the circadian clock, increasing stress and interfering with cognitive processes when interrupted. For this study, the focus was on lifestyle, nutritional, and environmental factors.

Childhood obesity is an avoidable health inequality due to varying socioeconomic statuses (Pearce et al., 2019). Jo (2014) showed that children generally start kindergarten at a similar weight. Still, by the eighth grade, children from low-income families are more likely to become obese than their peers from high-income families (Jo, 2014). Although certain racial and ethnic groups may have a higher prevalence of childhood obesity, this disappears when family income is controlled, suggesting that socioeconomic status plays a prominent role in the childhood obesity epidemic (Guarnizo-Herreño et al., 2019; Rogers et al., 2015). Low-income families have significantly higher rates of childhood obesity.

Adequate nutrition is essential for children to obtain critical nutrients for growth and development. Excessive intake of food or calories increases the risk of obesity. According to the dietary guidelines by United States Department of Agriculture (USDA) (2020), females aged 2 to 4 years require 1,000 to 1,400 calories per day. In contrast, males of this same age require about 1,000 to 1,600 calories per day. Likewise, female school-aged children, ages 5 to 8, need about 1,200 to 1,800 calories per day, with males the same age requiring about 1,200 to 2,000 calories per day. For children in later childhood and early adolescence, ages 9 through 13, females need 1,400 to 2,000 calories per day, with males the same age requiring 1,600 to 2,600 calories per day. For adolescents aged 14 through 18, females require about 1,800 to 2,400 calories per day, while males require 2,000 to 3,200 calories per day. For a child or adolescent eating 2,000 calories per day, only 12% of calories should come from sources not meeting food group requirements (USDA & United States Department of Health and Human Services, 2020). These calories would optimally come from nutrient-dense foods that provide health-promoting components such as vitamins and minerals and have little added sugars, sodium, or saturated fat. Appropriate growth and development are dependent on adequate nutrition for children and youth (Schwarzenberg & Georgieff, 2018).

Environmental factors may play a part in the increased prevalence of obesity. These environmental factors, such as food prices or access, technology, family structure, and the built environment, have played a part in people's inability to make the short-term changes needed for long-term health (Anderson et al., 2019). Anderson et al. (2019) explained that almost 40% of the growth in obesity may be attributed to decreasing food costs, coupled with an increase in sedentary lifestyles. Technology plays a severe role in sedentary lifestyles. Increased television viewing over time is a predictor of BMI increases (Anderson et al., 2019). Stahlmann et al. (2020) noted that children from nontraditional families, such as single-parent and blended families, have a higher prevalence of obesity than those from traditional family units. The CDC (2011) explained that the built environment includes all the physical parts where one lives and works. School is a considerable portion of their built environment; the school food environment and access to exercise opportunities also influence childhood obesity. Although adults are generally allowed to make unhealthy decisions fully knowing the consequences, children do not have this freedom. Obesity patterns are set by the age of 11; therefore, it is imperative that interventions to prevent obesity be implemented in childhood (Anderson et al., 2019). It is unknown how the timing of meals affects student obesity; I looked at this relationship and provided guidance on meal timing to address the potential association between meal timing and obesity. Eating meals at regular intervals may help establish healthy eating patterns to stave off obesity risks.

Implications

Obesity is linked to morbidity, mortality, and increased medical costs. According to 2006 Medicaid data, obese children account for $6,730 annually in health care costs, $4,284 more than the health care costs of normal-weight children (as cited in Smith & Smith, 2016). Further, in a 2020 study by Biener et al., obesity in youth raised annual medical care costs by $907 from 2001 to 2015 in all major categories: outpatient doctor visits, inpatient hospital stays, and prescription drugs. Hruby and Hu (2015) estimated that for an obese 10-year-old today, the medical costs attributed to obesity (upper estimate of $39,000) would pay for 2 years of public college tuition. In the future, medical expenditures related to obesity, which currently account for 9% of medical spending, nearly $2.0 trillion U.S. dollars in 2012, and will only continue to increase as a larger population of obese children become obese adults (Hoelscher et al., 2015; Segal et al., 2021). Establishing healthy eating patterns in childhood may reduce childhood obesity, lowering the costs associated with treating weight-related illnesses. By examining the timing of meals during the school day, I aimed to explore the contribution school lunchtimes have on eating patterns and the association this school eating pattern has to student BMI. As obesity increases the risks of chronic diseases, establishing normal eating patterns in childhood may help decrease this risk of obesity and lower medical expenditures related to obesity over the lifetime.

Maintaining a healthy weight decreases the chance of adverse chronic health conditions. Afshin et al. (2019) discovered that one in five deaths globally are associated with poor diet. As childhood obesity can lead to adult obesity, children with obesity are more likely to suffer from many chronic illnesses. Being at an unhealthy BMI in young adulthood can lead to adverse reproductive outcomes, long-term risk of Type 2 diabetes, and cardiovascular disease (Larson et al., 2016). Likewise, excessive energy intake can lead to triglyceride depositions in adipocytes (Pandolfi et al., 2016). These deposits can lead to severe metabolic abnormalities, increasing the likelihood of cardiovascular diseases, cerebrovascular diseases, kidney dysfunction, insulin resistance syndrome, and Type 2 diabetes mellitus. Given the documented adverse outcomes associated with childhood obesity, it is vital to examine the causes of childhood obesity to address and combat these negative health outcomes. In this study, I examined lunchtimes of students across the United States and the association these times have on student BMI.

School Meals and Children's Body Weight

The school environment plays an essential role in children's diets and overall health. The USDA sponsors several programs for children to receive meals at school for a reduced or no cost. These meals are designed to ensure that school-aged children have access to nutritious meals and snacks that support normal growth and development (Fox & Gearan, 2019). Two such programs are the National School Lunch Program (NSLP) and the School Breakfast Program (SBP). Both programs provide a "nutrition safety net" for low-income children and provide up to 58% of daily calorie intake (Cullen & Chen, 2016, para. 1). Healthier meals served at school can potentially reduce the risk of obesity (Kenney et al., 2020).

History of School Meals

The NSLP began in 1946 under the National School Lunch Act, intending to reduce food insecurity. The NSLP operates in over 100,000 public and private schools across the United States, serving over 31 million students (Gundersen, 2015). The benefit of the NSLP is that by offsetting the student's cost, the family then has more money to spend on food for the family, reducing food insecurity for the household, not just the student served. While the impact of this compensation is not immediately apparent, the NSLP has reduced the incidence of food insecurity among households with school children by 2.3% to 9% (Gundersen & Ziliak, 2018). The NSLP provides free or reduced-cost lunches to millions of children, combatting food insecurity throughout the school year (Cullen & Chen, 2016).

The federal SBP began subsidizing breakfast for qualifying children in 1966. The SBP is a separate program from the NSLP, with schools having the option to run one program or both. The goals of the SBP were to reduce food insecurity, improve nutrition, and facilitate learning by providing a meal for students before school started, often after long morning bus rides (Corcoran et al., 2016). The SBP is designed to serve students before school; this may be too early for some students. To make breakfast even more available to students, some school districts have implemented Breakfast in the Classroom (Moeltner et al., 2019).

Nutritional Content of School Lunches

Improvements to the NSLP have reduced meal disparities in schools. The USDA estimated in 2017 that 16.4% of households with children younger than 6 years experienced food insecurity (as cited in Drennen et al., 2019). The NSLP is crucial for providing adequate nutrition for these food-insecure, often low-income children. The USDA updated the NSLP nutritional standards in 2012, which had not been updated since 1995. The meals prior to 2012 were high in sodium and fats. The new criteria included offering fruits and vegetables daily, ensuring that half of the grains must be whole grain-rich, providing a weekly range of meat/meat alternates with a daily minimum, offering only fat-free and low-fat kinds of milk, allowing zero grams of trans fat per portion, and enforcing weekly calorie and saturated fat limits (Cullen & Dave, 2017). Fully implemented and compliant NSLP standards could improve school nutrition for students participating in the NSLP.

Length of Time for Meals

Increasing the time children have to eat lunch at school may reduce the prevalence of childhood obesity, reducing the costs associated with treating weight-related illnesses. In the seminal study by Trasande and Chatterjee (2009), the estimated cost to treat overweight children for 2 years is close to $79 per child. Hayes et al. (2016) discovered that over 3 years, the cost to treat children with obesity was $4,124, almost $2,000 more than the healthcare costs of healthy-weight children. In a seminal study, Bhatt (2014) used this to estimate that an increase of 10 minutes to a child's school lunch period could save nearly 33 million dollars over those 2 years. Likewise, using the findings from Geier et al. (2007) and An et al. (2017) that overweight children miss 1.7 more days than their normal-weight peers, an additional 10 minutes for lunch could reduce the number of absences by close to 700,000 days per year (Bhatt, 2014).

According to Cohen et al. (2016), there are no national standards for school lunch length. They reported that a substantial number of students had insufficient time to eat, which decreased entrée, milk, and vegetable consumption compared to students who had more time to eat. An adequate amount of time to eat lunch allows students greater access to healthful options and yields significant benefits like healthy dietary behaviors and better weight outcomes (Turner et al., 2018). Cohen et al. (2016) suggested that a lunch period of at least 25 minutes would reduce food waste and improve dietary intake. Likewise, Ang et al. (2019) indicated that school lunch periods should be increased to a more extended 30-minute period. This increase was also recommended as scheduled lunch periods include times students must wait in line, not purely the time students can eat (Ang et al., 2019). Burg et al. (2021) discovered that children with 20 minutes of seated lunch consumed more fruits and vegetables and had less waste than those with only a 10-minute seated lunch. Research shows that elementary students consume more foods rich in nutrients, like calcium and vitamin A, when they have 30 minutes for lunch instead of 20 minutes. As schools are often crunched for instructional time, insufficient time for lunch may be a reason schools serve meals too early or too late.

Positive changes can be made in children's dietary behavior through nutrition interventions focused on school settings and parental involvement. These changes could subsequently reduce the prevalence of childhood obesity (Saha et al., 2020). By investigating the timing of meals in relation to BMI, I aimed to test the association between eating at certain times and the effect this may have on BMI for children and youth. Eating at certain times may increase or decrease the chance of developing these chronic diseases that are associated with obesity and high BMIs. From this proposed study, school administration and parents will have access to more information on the timing of meals related to childhood obesity and may use the findings to implement policies to ensure that students eat meals at the optimal time.

Association Between the Timing of Meals and Obesity

Energy Intake and Diet Quality

Studies have shown that when we eat, not just what we eat, has a significant role in weight gain and obesity treatment (St-Onge et al., 2017; Goheer et al., 2021). Energy metabolism is linked to different levels of the circadian clock: behavioral, physiological, and molecular. Ruiz-Lozano et al. (2016) evaluated food-timing in bariatric surgery patients after six years. They discovered that less weight was lost in those who ate their main meal later in the day. The authors posited that eating a late lunch was associated with decreased resting energy expenditure, fasting carbohydrate oxidation, and glucose tolerance.

The daily rhythm of feeding and fasting could prevent weight gain. In a systematic review by Zou et al. (2019), the researchers examined the association between child adiposity and calorie intake, timing, and meal frequency in the evening. Their review aimed to better understand the role of night eating on adiposity, as the evidence base for the recommendation of across the day energy distribution has not been studied. Likewise, Karatzi et al. (2017) revealed that data for children on late-night calorie consumption is limited. In their study of Greek children aged 9 to 13 years, late-night overeating was associated with consuming a smaller breakfast or skipping breakfast altogether. This late overeating, coupled with low physical activity levels, led to an increased risk of higher BMI. Developing healthy eating habits early in life is vital to prevent the onset of diet-related diseases. Early eating habits are directly related to eating habits in adulthood (Zou et al., 2019).

Recess before lunch, known as *reverse recess*, may also play a role in student weight status and energy imbalance. Mathieu et al. (2018) observed a lower energy balance for children who exercised immediately before a meal. The National Cancer Institute (n.d.) defined energy balance as “the state at which the number of calories eaten equals the number of calories used" (para. 1). Albert et al. (2015) also discovered an 11% reduction in overall energy intake for their sample of 15-20-year-old boys when exercises were performed immediately before the meal and a reduction of approximately 170 kcal when the activity was performed immediately before lunch compared to those who had a 135-minute delay between the meal and exercise—reversing recess to before lunch increases fruit and vegetable consumption and decreases waste (Chapman et al., 2017). Teachers also perceived this reverse recess to benefit classroom behavior and readiness to concentrate after lunch (Green et al., 2019). These benefits included decreased plate waste, increased consumption of nutrients, reduced discipline problems on the playground and in the lunchroom. Reversing recess to before lunch instead of after helps regulate energy imbalance, increase healthy consumption, and decrease behavioral issues.

Snacks are often associated with excessive energy intake, which often leads to overweightness and obesity. Shriver et al. (2018) determined that more than a quarter of American children's daily energy intake comes from snacks. These snacks are often high in sugar, fat, and sodium. This increase in snacking may be attributed to changes in the frequency of main meals (Larson et al., 2016). However, snack consumption can promote satiety at regular and consistent times and decrease caloric intake at the next meal (Larson et al., 2016). Regular and consistent is critical, as irregular eating habits become common during adolescence and can increase the risk of becoming overweight (Larson et al., 2016).

Children are guided by environmental constraints regarding when and how much to eat. Castellari and Berning (2016) conducted a study with fourth-grade classes to analyze whether a nutritious snack offered one hour before lunch affected the students' hunger and lunchtime consumption level. They discovered that students shifted their caloric and nutrient intake from lunch to snack time, reducing student hunger. If lunch is the first meal a child gets in the day, they are more likely to be hungry or make poor food choices. School eating schedules at off times, those before 11 a.m. or after 2 p.m., could affect a child's natural response to hunger and lead to overconsumption (Castellari & Berning, 2016).

Trends show that people are consuming meals much later in the day. Eating later in the day has been associated with higher odds of being overweight or obese, impaired glucose tolerance, and insulin secretion (Lopez-Minguez et al., 2019). Xiao et al. (2019) discovered that those who consumed more during the morning were associated with lower odds of being overweight or obese. Those who consumed more of their energy intake during the night window were associated with higher odds of being overweight or obese. One reason more calories are consumed at night maybe that day meals occur too early or too late.

Sleep also plays an essential role in meal timing. Later bedtimes may also lead to later mealtimes and greater daily fat intake. Spaeth et al. (2019) showed that later bedtime, not necessarily sleep time, correlated with greater daily fat intake, later breakfast, and greater after-dinner snacking. The researchers suggested children who skip breakfast often increase evening caloric intake, which is associated with being overweight or obese (Spaeth et al., 2019). Skipping breakfast may push students to eat more later in the day. Eating the bulk of the day's calories in the evening may mean students are also pushing back bedtimes until much later in the evening. Spaeth et al. (2019) suggested that children who eat breakfast daily tend to have earlier bedtimes. The researchers showed that later sleep is associated with later meal timing, which is associated with overweight and obesity. I examined early and late lunch timing and the association this may have to child and youth BMI. Children with later bedtimes may consume more calories at night, leading to less consumption during the school day or over consumption when night calories are combined with calories from meals during school time. This is especially problematic when school meals are served outside of traditional lunchtimes, like before 11 a.m and after 1 p.m. Eating before 11 a.m. may increase student hunger for the afternoon and evening, while eating after 1 p.m. may increase hunger during the morning and push back energy intake later into the evening.

Meal Timing and Obesity

Chrononutrition is the study of meal timing on metabolism, obesity, and weight loss (Lopez-Minguez et al., 2019). Jakubowicz et al. (2013) conducted one of the first studies identifying the effect of caloric distribution throughout the day and weight loss. Subjects were overweight and obese women, aged 30 to 57, with metabolic syndrome who ate a high caloric breakfast and low caloric dinners (700 kcal breakfast, 500 kcal lunch, 200 kcal dinner) lost significantly more weight with a reduced waist circumference than those who consumed low caloric breakfasts and high caloric dinners (200 kcal breakfast, 500 kcal lunch, 700 kcal dinner). Similarly, Kahleova et al. (2017) discovered that those who consumed breakfast as the largest meal experienced a significant decrease in BMI than those who ate their largest meal at dinner. Even those who consumed a big lunch experienced a more minor but still significant reduction in BMI than those who ate dinner as the largest meal of the day. Children attend school during the time associated with breakfast and lunch, which is the optimum time for calorie consumption. Ensuring that breakfast and lunch are served at appropriate times encourages students to consume calories during this optimum time. Serving lunch too early may shift consumption of calories to the evening time, increasing the risk of weight gain.

Schools are not mandated on when they should serve meals during the day. Environment and Human Health, Inc. (2004) stated that there are no federal requirements regarding the time of day that schools should serve lunch, only recommendations; therefore, lunch period start times vary dramatically throughout the United States. The National School Lunch Program's (2021) federal recommendations indicate that lunch should be served to students daily between 10 a.m. and 2 p.m.

The time-of-day calories are consumed influences weight gain and obesity. Lopez-Minguez et al. suggested that the timing of eating may determine fat accumulation and mobilization. Garaulet et al. (2013) concluded that late lunch eaters (after 3 p.m.) were less likely to lose weight than early lunch eaters (before 3 p.m.), controlling for age, appetite hormones, energy intake and expenditure, sleep duration, and macronutrient distribution. However, Agustina et al. (2020) discovered that adolescent girls aged 12-19 years have greater odds of being overweight or obese if they skip dinner. Interestingly, less eating frequency led to lower energy intake, yet the likelihood of being overweight or obese increased. Zalewska and Maciorkowska (2017) showed that students who had lunch and dinner later and skipped breakfast were more likely to be overweight and obese. Normal weight children also ate lunch more regularly than overweight and obese students. Zalewska and Maciorkowska (2017) also suggest that overweight and obese children accumulate meals and eat the bulk of their energy intake in the afternoon. As Lopez-Minguez et al. (2019) stated, animals choose to eat depending on food availability, yet schools dictate food availability for children. Adults who skip meals are more likely to be obese due to overeating at other meals; this is also true for children with low physical activity levels (Karatzi et al., 2017). The time-of-day calories are consumed influences weight gain and obesity. Students do not decide when to eat, but schools can encourage a regular meal pattern by providing breakfast and lunch at appropriate times.

The timing of lunch was associated with consumption in the research by Chapman et al. (2017). Students with early lunch periods consumed 5.8% less of their entrees and 4.5% less of their milk than those with midday lunch periods. In comparison, students with late lunch periods consumed 13.8% less of their entrees and 15.9% less of their fruit than students with midday lunch periods. Bhatt (2014) indicated that reductions in BMI might be associated with the shift of consumption when students have more opportunities to expend calories. Opportunities for physical activity happen during the day like Physical Education class and recess, or when it is light outside for children to play. The majority of these daylight hours are during the school day. Spreading meals out throughout the school day gives students opportune time for energy intake and expenditure. Constrained and off-schedule lunch periods, those lunches served before 10 a.m. or after 2 p.m. can alter students' appetites and have a negative impact on focus and mood in the classroom.

Students are no longer constrained to school mealtime scheduled during school vacations, such as summer and winter break. Weaver et al. (2020) showed in their study that children's BMI accelerated during the summer break from school. The authors used the Structured Days Hypothesis to explore the impact of the lack of structure during summer breaks. They found that the lack of structure harmed children's obesogenic behaviors, including physical activity and diet. Weaver et al. (2020) suggested that the increase in sedentary behavior over the summer, accompanied by poor nutrition, may contribute to weight gain and BMI. Similarly, Brazendale et al. (2021) discovered that childhood obesity behaviors, such as physical activity, are more favorable on more structured days, such as school days, than on weekends or days with less structure. The structure of school, meals, mealtimes, and programming positively impacts children's obesogenic behaviors and moderates summer BMI increase.

In reviewing the research, there is a gap in the findings on individual weight status and how people perceive their mealtimes. In a phenomenological study, Suiraoka et al. (2017) discovered that parents perceive that if a child does not eat a meal or does not eat much of the meal, he will overeat at the next. When lunch is served too early, when students are not hungry, they may eat very little of the meal, leading to overeating at the next meal. However, researchers have yet to identify how people perceive meal times, too early or too late, and the relation to obesity. This study is designed to explore students' perception of when they eat and the association to their BMI.

Definitions

Adolescence: A period following the onset of puberty during which a child develops into adulthood; a pivotal period in which many health risk behaviors are initiated (Zheng et al., 2016). The age span can vary between individuals but is generally between 10 and 19 (American Psychological Association [APA], 2020a).

Body mass index (BMI): A widely used measure of adiposity or obesity based on the following formula: weight (kg) divided by height squared (m^2) (APA, 2020b).

Childhood: The period between the end of infancy and the onset of puberty, marking the beginning of adolescence. Generally, from about two years to 10 to 12 years of age (APA, 2020c).

Childhood obesity: A BMI at or above the 95^{th} percentile for children and teens of the same age and sex (CDC, 2018).

Childhood overweight: A BMI at or above the 85^{th} percentile and below the 95^{th} percentile for children and teens of the same age and sex (CDC, 2018).

Obesity: A BMI at or above the 95^{th} percentile of the CDC sex-specific BMI-for-age-growth charts (CDC, 2019).

Socioeconomic status: The social standing or class of an individual or group, often measured as a combination of education, income, and occupation (APA, 2022).

Assumptions

The study used secondary survey data, which conveys particular assumptions. One assumption was that survey respondents were honest with their answers. Another assumption for this study was that the sample size is representative of the population. As the SNDA-III collected a broad range of data from nationally representative samples of public-school food authorities, schools, students, and parents, I assumed that the results of this study are reliable and may be generalized to similar populations.

Scope and Delimitations

Childhood obesity continues to be a highly studied public health topic. While meal timing has been limitedly studied in the adult population, little is known about meal timing in children and adolescents and how school mealtimes play a role in childhood obesity. This study is an opportunity to bridge the gap in the literature on childhood obesity and meal timing. Furthermore, this study has the potential to show the importance of this issue and bring about policy and social change surrounding school meal schedules.

The data for this study were taken from the 2004-2005 SNDA-III. The SNDA-III data was not collected to address my particular RQs. As the survey used a sampling technique, it is possible that not all population subgroups or all geographic areas within the United States were included in the sample. As I did not collect this data, I may also be unaware of any specific nuances in the data collection process (Cheng & Phillips, 2014).

Limitations

The data set for the analysis was restricted to the 2004-2005 SNDA-III data set because this was the most current data set publicly available. This could be a limitation as the data set only contained a single school year of survey data. Conclusions from the interpretation of this data must be construed guardedly to avoid over-or underestimating associations based on a single point in time. As only 2,314 child/youth surveys were submitted, meaning there may be sectors of students not adequately represented.

Significance

This study is significant because research on meal timing and obesity in children and adolescents is limited to the best of my knowledge. Bhatt (2014) indicated that further studies were needed on the spacing of lunch between the beginning and end of the school day. Chapman et al. (2017) also suggested that future research regarding school meals should consider the challenges of early and late lunch periods. The significance of this study is that it may provide a better understanding of the timing of meals in school and how meal timing may impact students' health. This study may add to public health by providing evidence of factors contributing to childhood obesity. Findings from this study may foster the development of school day schedules that better meet the needs of students. This study's social change implications include raising awareness of scheduled mealtimes, spreading mealtimes throughout the day for children decreasing periods of increased hunger, and enabling schools and parents to recognize and intervene in practical ways to combat childhood obesity. For school-aged children, the results from this study could lead to interventions that allow students to consume meals at regular intervals. Eating at adequately spaced-out mealtimes may decrease extended periods that could lead children to increased hunger or overconsumption. These periods of increased appetite that lead to overeating could lead to an increased chance of obesity. Establishing healthy routine eating patterns as children gives them a foundation to continue these healthy patterns into adulthood. As children are not in school on weekends or breaks, a normative lunchtime established in school prepares children to eat meals at these times at home as well.

Summary and Conclusions

While there have been significant studies on how much children eat during meals, very little research has been done on the time-of-day meals are consumed. Likewise, obesity research and timing of meals have almost exclusively targeted adults, not youth. Furthermore, most studies on food behaviors focus on individual-level factors. Children are still very much regulated by home and school environments when it comes to meal timing. School-provided meals are where some low-income students get the bulk of their food. These low-income children may not get a meal at home or limited food at dinner. If lunch is served early, these students may go hours until their next school-provided meal. This food insecurity can cause excessive hunger and lead to poor overeating habits when food is available.

My research revealed a gap in research on the timing of meals, specifically lunch, and childhood obesity. Given the risk childhood obesity has on health throughout the lifespan, this study is needed. I believe the findings will fill gaps in knowledge about the role meal timing has on obesity and help parents and school personnel understand the best timing for energy intake across the day, thereby helping them to prevent adulthood obesity and related chronic disease in their children.

Section 2: Research Design and Data Collection

Introduction

I conducted a cross-sectional quantitative analysis to explore and describe the association between the independent and dependent variables. Specifically, I aimed to examine the impact of the timing of school lunches concerning the prevalence of childhood obesity in school-aged children when controlling for age, gender, race, and socioeconomic status. To do that, a secondary data set of quantitative data from the SNDA-III was the primary source of data for this investigation. This section of my research focuses on the research design and rationale, methodology, population, sampling procedures, instrumentation and operationalization of constructs, data analysis plan, threats to validity, and ethical procedures.

Research Design and Rationale

I conducted a cross-sectional study using quantitative research analysis of an existing secondary data set for this research. Implementing this approach had the potential to bridge a gap in the literature on the selected topic as most researchers have not looked at the child, youth, or school population specifically. The primary source of secondary data used to investigate the association between mealtimes and childhood obesity were retrieved from the 2004-2005 SNDA-III. The independent, or predictor, variable for RQ1 was the time lunch is served. The independent variable for RQ2 was how students perceive the timing of school lunches. The dependent variable for all RQs was child/youth BMI. The covariates were age, gender, race, and socioeconomic status.

As childhood obesity continues to be a significant public health issue, scholars must pay more attention to the challenges children and youth face.

Methodology

Population

The population group for this study consisted of American primary and secondary school students. Researchers have aimed to collect a broad range of data from nationally representative samples of public School Food Authorities (SFA), schools, students, and parents in school year 2004-2005. All participants who answered the child/youth interview completely were included within the sample, including 2,314 child/youth interviews. Exclusion criteria included those who did not have a BMI due to missing or implausible height, weight, and/or age values. Of the 2,314 child/youth interviews, 81 were excluded due to missing or implausible data.

Sampling and Sampling Procedures

In this study, I used publicly archived data from the USDA SNDA-III national study. Requests were made to the Food and Nutritional Services Division of the USDA. Access to the dataset was granted through CloudVault. This is the only national survey with the independent and dependent variables of interest to my study, to the best of my knowledge. The SNDA-III is a nationally representative cross-sectional study with a 3-stage sample design. This design allowed a description of the district and school food environments. The SNDA-III contains data from 130 SFAs, 398 schools, and 2,314 public school students in Grades 1 through 12. Districts responded with an 83% response rate, schools 95%, and students 63%. Student response rates were constrained by consent issues and school schedules (see Gordon et al., 2009).

The SNDA-III was designed to be representative of all public SFAs that participate in the NSLP, schools in these SFAs, and first through 12th graders in those schools. Sample sizes were chosen to detect statistically significant differences and the best feasible precision for school-level estimates. Students were randomly sampled from schools within the sampled SFAs. Student-level data were collected on-site in a random subset of 287 schools. SFAs and schools were not selected with equal probability; therefore, the sample was reweighted so that students in the population were equally represented and adjusted for nonresponse (see Gordon et al., 2009).

The 2004-2005 SNDA-III data were collected from January to June 2005. The USDA Food and Nutrition Service, the 2004 Education Information Advisory Committee of the Council of Chief State School Officers, and the Office of Management and Budget approved the study’s procedures. The researchers also worked with any institutional review process a school district required. Researchers used either active or passive consent procedures to gain consent from parents or guardians for student-level data collection. No student-level identifiable information is publicly accessible.

Justification for the Effect Size, Alpha, and Power Levels

In research, a sample of the population is studied to infer something about a population (Patino & Ferreira, 2016). For a sample to be representative of the target population, an appropriate number of participants must be included in the sample, large enough that the chance of not finding differences between groups is low and detecting significant differences is high (Patino & Ferreira, 2016). Power analysis is used to determine the sample size needed to guarantee the outcome has the anticipated power based on the selected effect size. Power of at least 80% was used to ensure a high probability of detecting the effect. In comparison, the critical level of significance is usually ≤ 5% (Patino & Ferreira, 2016).

The SNDA-III was designed to obtain information from 138 unique SFAs, 398 schools, and 2,314 students. I performed a power analysis using G*power software (see Faul et al., 2009). A G*power priori analysis for logistic regression with a two-tailed alpha of 0.05, an odds ratio of 0.8, and a power of 80% yielded a minimum sample size of 994. The power analysis determined that the minimum sample size should be 994. Still, the sample used within this research was more significant.

Instrumentation and Operationalization of Constructs

The SNDA-III was a nationally representative study conducted in 2004-2005 and funded by the USDA. The SNDA-III is the third iteration of the SNDA, which began in the 1991-1992 school year. The SNDA-I examined school meals and dietary intakes of schoolchildren. This SNDA-I helped prompt school meal initiative reforms (Gordon et al., 2009). The SNDA-II collected data from the 1998-1999 school year and found that schools had improved in meeting nutrition goals. However, policy objectives were still lacking (Gordon et al., 2009). The SNDA-III consists of data related to staff, menus, and students. In this study, I used the student-level data. The focal point of the student interview was the 24-hour dietary recall interview that was conducted in person. The interviewers used the Automated Multiple Pass Method (AMPM) software from the

Agricultural Research Service Food Surveys Research Group. The AMPM is a research-based, multiple-pass approach that employs five steps to enhance complete and accurate food recall while reducing respondent burden (USDA, 2021). Blanton et al. (2006) and Rhodes et al. (2013) showed the validity of the AMPM regarding group total energy, nutrient, and sodium intake. The AMPM has been used yearly since 2002 for the What We Eat in America, NHANES, with two recalls a year including 5,000 individuals. Interviews were conducted in school, followed by height and weight measurements. Field interviewers used standardized equipment and procedures for measuring student height and weight.

Variables

The independent variables were all related to the time lunch is served. For RQ1, the independent variable was the time lunch is served. The independent variable for RQ2 was student perceived timing of when lunch is served.

The dependent variable for all RQs was child/youth BMI. This variable was calculated from child/youth weight and height. The BMI was then converted to BMI percentiles with three categories: < 85% representing a normal BMI, ≥ 85% < 95% representing those students at risk of being overweight, and ≥ 95% meaning obese. Gallagher (2020) explained that while classifying children and youth into BMI categories is not as simple as the adult categories, an expert committee comprised of representatives from 15 professional organizations defined obesity as BMI ≥ 95^{th} percentile or an absolute BMI ≥ 30 kg/m^2, whichever is lower based on age and sex. Table 1 shows the operationalization of variables.

Table 1

Operationalization of Variables

Variable name/type	Categorization and operationalization	Level of measurement
BMI percentile (dependent variable)	Body Mass Index: < 85% = 1, ≥ 85% < 95% = 2, ≥ 95% 3	Nominal
Perceived mealtime (independent variable)	Lunch period too early in the day, too late, or about right? Too early = 1, Too late = 2, About right = 3	Nominal
Recode time lunch is served (independent variable)	Before 11 a.m. = 1, 11 a.m. to 1 p.m. =2, After 1 p.m. = 3	Nominal
Age (covariate)	Student's age in years	Ratio
Gender (covariate)	Student's gender: 1=male, 2=female	Nominal
Race (covariate)	Student's racial category: 1 = Asian, 2 = American Indian/Alaska Native, 3 = Black/African American, 4 = Native Hawaiian/Pacific Islander, 5 = White, 6 = Other	Nominal
Socioeconomic status (covariate)	Income proportionate to 2004 federal poverty guidelines (percent)	Nominal

Research Questions and Hypotheses

RQ1: Is there a significant association between the time school lunches are served and student BMI when controlling for age, gender, race, and socioeconomic status?

$H_0$1: There is no significant association between the time school lunches are served and student BMI when controlling for age, gender, race, and socioeconomic status.

H_A1: There is a significant association between the time school lunches are served and student BMI when controlling for age, gender, race, and socioeconomic status.

RQ2: Is there an association between perceived meal timing and student BMI controlling for age, gender, race, and socioeconomic status?

$H_0$2: There is no association between perceived meal timing and student BMI when controlling for age, gender, race, and socioeconomic status.

H_A2: There is an association between perceived meal timing and student BMI when controlling for age, gender, race, and socioeconomic status.

Data Analysis

Data analysis was completed using IBM SPSS Version 28. Once approval from Walden Institutional Review Board was obtained, the data were downloaded and screened for completeness, accuracy, and consistency across the two data sets. This included solidifying variables of interest and recoding as needed to make data appropriate for analysis. Participants with missing or invalid data were excluded from the study. Only publicly available data were used with confidentiality and anonymity measures already accounted for.

I used quantitative data analysis to answer the RQs. To describe and understand the sample population, an analysis of descriptive statistics was done first. Analysis included logistic regression tests to answer if there was an association between meal timing and obesity. Multinomial logistic regression does not assume normality, linearity, or homoscedasticity, but does have the assumptions of independence among the dependent variables, which can be tested with the Hausman-McFadden test (Starkweather & Moske, 2011). Multinomial logistic regression also assumes nonperfect separation (Mansournia et al., 2018). Multinomial logistic regression requires a sample size of a minimum of 10 cases per independent variable (Starkweather & Moske, 2011).

Childhood obesity is a complex public health issue with several contributing factors. To account for this, I chose covariates to account for any potential association between the independent and dependent variables despite these covariates. These covariates included age, gender, race, and socioeconomic status, all of which have been identified in previous research (see Anderson et al., 2019; CDC, 2019; Drennen et al., 2019; Hayes et al, 2016; Hoelscher et al., 2015; Llewellyn et al., 2016; Rogers et al, 2015; Sanyaolu et al., 2019).

The statistics were interpreted based on the standard alpha of 0.05. Consequently, if the *p*-value was above 0.05, the null hypothesis would be retained. Goodness-of-fit tests and parameter estimates were used to interpret the loglinear analysis. For the multinomial logistic regression, the goodness-of-fit, model fitting information, pseudo *r*-

square, likelihood ratio tests, and parameter estimates were used to interpret the results (see Alexopoulos, 2010).

Threats to Validity

Quantitative research has the potential for a broad array of threats to validity (Babbie, 2016). Creswell (2014) defined internal validity as any potential factors that could threaten the researcher's ability to interpret statistical results. One internal validity consideration for this study was potentially the subject population's size, characteristics, and recall bias. Selection bias is also a threat to validity, as secondary data were used in this study. External validity is the degree to which the research results can be generalized to other populations (Creswell, 2014). While the SNDA-III is a nationally representative survey, it would not generalize to other populations outside the United States. There is also a chance of nonresponses and underreporting that could threaten validity. While all efforts were made to increase internal and external validity, the study's limitations note the risk of validity concerns.

Ethical Procedures

Ethical considerations were judiciously considered for this study. The SNDA-III data are available for public use through the USDA. Permission was granted through CloudVault directly from the USDA. The secondary data in the SNDA-III were coded to protect identities, and students were given a participant ID to provide anonymity (USDA 2007)). The anonymity of participants was ensured to protect the right of privacy for each participant. Continuous variables that might allow deductive disclosure of a student's identity were grouped or converted into percentages while file identifiers and related variables were reset so that they could not be traced back to specific individuals. Consent was given for any disclosed, identifiable responses (see Gordon et al., 2009). A Walden Institutional Review Board (IRB) application 04-21-22-1004057was submitted and approved before data analysis and reporting of the data results.

Summary

In this section, I discussed the methodology of this research project, including the research design, analysis strategies, validity, and ethical considerations. I used univariate and bivariate analyses to answer the RQs. The sample population included students with completed child/youth interviews and plausible height and weight responses who participated in the NSLP across the United States. The independent variables were lunchtimes and perceived lunchtimes. The dependent variable was student BMI. The covariates were age, gender, race, and socioeconomic status. I explained the operationalism of the constructs and the analysis methods that were used to answer the RQs. Finally, internal and external validity, as well as ethical procedures, were considered. In Section 3, I present the statistical analyses from this study and my research findings.

Section 3: Presentation of the Results and Findings

Introduction

The purpose of this quantitative doctoral study was to examine the associations between lunch timing and student BMI. The study participants were students in public schools in the United States who participated in the SNDA-III survey. I used SPSS Version 28 (IBM Corp, 2022) to answer the RQs and to test the hypotheses, which included the following:

RQ1: Is there a significant association between the time school lunches are served and student BMI when controlling for age, gender, race, and socioeconomic status?

$H_0$1: There is no significant association between the time school lunches are served and student BMI when controlling for age, gender, race, and socioeconomic status.

H_A1: There is a significant association between the time school lunches are served and student BMI when controlling for age, gender, race, and socioeconomic status.

RQ2: Is there an association between perceived meal timing and student BMI controlling for age, gender, race, and socioeconomic status?

$H_0$2: There is no association between perceived meal timing and student BMI when controlling for age, gender, race, and socioeconomic status.

H_A2: There is an association between perceived meal timing and student BMI when controlling for age, gender, race, and socioeconomic status.

In Section 3, I present the results and findings from this study. This section includes the data collection process, which contains data collection time frames, recruitment and response, discrepancies from the original research plan, and descriptive analyses of the sampled population. This section concludes with a discussion of the results of the quantitative analyses that were used to answer the RQs.

Accessing the Data Set for Secondary Analysis

Data Collection Time Frame and Response Rates

In this study, I used the most current available data set that included school lunch times and corresponding student BMI, the SNDA-III from school year 2004-2005. The SNDA-III is a nationally representative cross-sectional study with a 3-stage sample design. This design allowed a description of the district and school food environments. The SNDA-III contains data from 130 SFAs, 398 schools, and 2,314 public school students in Grades 1 through 12. Students were randomly sampled from schools within the sampled SFAs. Student-level data were collected on-site in a random subset of 287 schools. SFAs and schools were not selected with equal probability; therefore, the sample was reweighted so that students in the population were equally represented and adjusted for nonresponse. No student-level identifiable information is publicly accessible. Districts responded with an 83% response rate, schools 95%, and students 63%. Student response rates were constrained by consent issues and school schedules (Gordon et al., 2009). The 2004-2005 SNDA-III data were collected from January to June 2005.

Discrepancies From the Original Research Plan

The study sample included all respondents to the child/youth interview from 287 schools. Respondents who did not have a lunch time, did not respond to perception of lunch time, and who did not have an accurate BMI were excluded.

Baseline Descriptive and Demographic Characteristics

The descriptive statistics of the study population are shown in Table 2. Respondents who were missing or had implausible BMIs, those who did not answer their opinion on timing of school lunch, and those without lunch times were excluded, bringing the sample size from 2,314 to 2,173. The total study population was 2,173, of which 50.2% were female and 49.8% were male. The population consisted mostly of White students (65.7%), but also included Asian (2.3%), American Indian/Native Alaskan (0.8%), Black (20.6%), Native Hawaiian/Other Pacific Islander (0.3%), and Other (10.2%). The mean age of respondents was 12.73 years, with the youngest respondent 5 years of age, and the oldest 19 years of age. Socioeconomic status was measured by percent against the poverty line; 31.8% of respondents were at or below 130% of the poverty line, 13.3% were at or below 185%, 18.4% were at or below 200%, 13.4% were at or below 300%, and 23.1% were above 300%.

Table 2

Descriptive Statistics of Characteristics of Study Population

Variable	Frequency	Percent
Age		
5 and 6 years old	47	2.2
7 years old	117	5.4
8 years old	137	6.3
9 years old	135	6.2
10 years old	121	5.6
11 years old	141	6.5
12 years old	216	9.9
13 years old	297	13.7
14 years old	272	12.5
15 years old	202	9.3
16 years old	218	10.0
17 years old	170	7.8
18 and 19 years old	100	4.6
Gender		
Male	1083	49.8
Female	1090	50.2
Race/ethnicity		
Asian/American Indian/Native Alaskan/Native Hawaiian/Other Pacific Islander	75	3.5
Black	448	20.6
White	1428	65.7
Other	222	10.2
Poverty		
<= 130 poverty line	691	31.8
<= 185 poverty line	288	13.3
<= 200 poverty line	400	18.4
<= 300 poverty line	292	13.4
>300 poverty line	502	23.1
BMI category		
Normal	1292	59.5
Overweight	366	16.8
Obese	515	23.7

Note. $N = 2{,}173$

Primary Univariate Analysis of Covariates

The covariates that have been identified in previous research as possibly contributing to childhood obesity include age, gender, race, and socioeconomic status. First, I performed univariate analyses to determine if the use of these covariates was acceptable within this study. Then, I used chi-square analyses to determine if the differences I discovered were significant. These analyses were used to test each covariate as it related to the dependent variable of student BMI.

Gender

Figure 2 shows that most students (60.6% of males, 58.3% of females) are in the normal weight category, not obese or overweight. Based on this analysis, 15.3% of males and 18.3% of females are considered overweight, while 24.1% of males and 23.3% of females are considered obese. Table 3 shows the crosstabulation of BMI category by gender. There was not a significant difference in BMI based on gender (p = .170) with a weak association (Cramer's V = .040; Table 4, Table 5). Females and males have roughly the same chance of being normal weight, overweight, or obese.

Figure 2

BMI Category by Gender

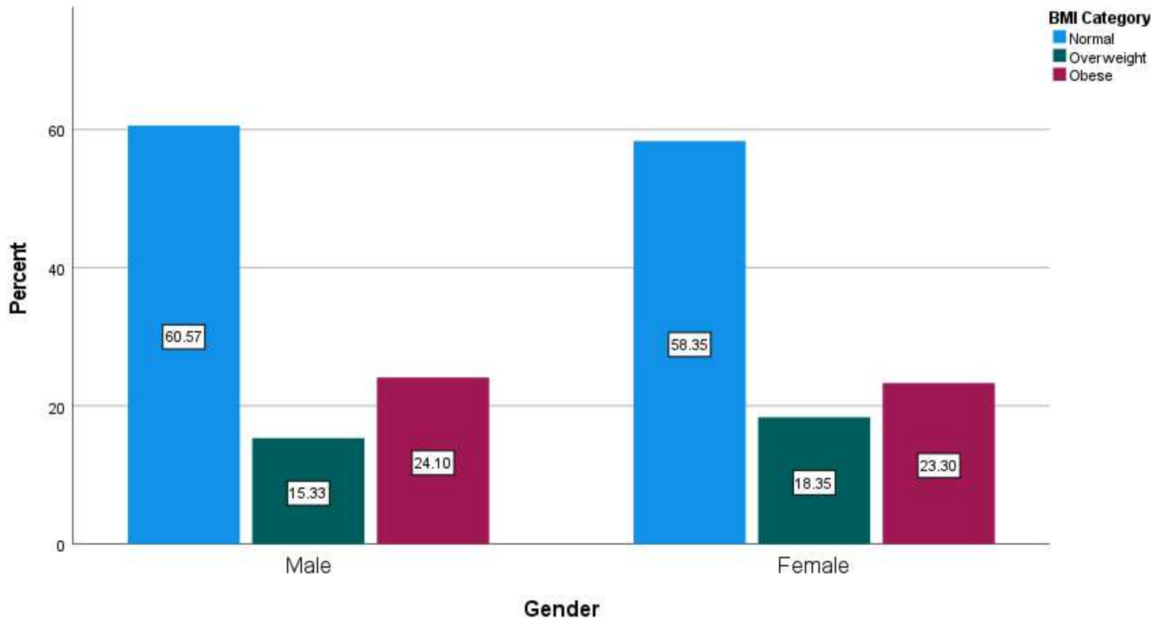


Table 3

Crosstabulation of BMI Category by Gender

		BMI category			
		Normal	Overweight	Obese	Total
Gender	Male	656	166	261	1,083
	Female	636	200	254	1,090
Total		1,292	366	515	2,173

Table 4

Chi-Square Analysis of BMI Category by Gender

	Value	*df*	Asymptotic significance (2-sided)
Pearson chi-square	3.541[a]	2	.170
Likelihood ratio	3.545	2	.170
Linear-by-linear association	.157	1	.692
N of valid cases	2173		

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 182.41.

Table 5

Effect Size of Chi-square Analysis of BMI Category by Gender

		Value	Approximate significance
Nominal by Nominal	Phi	.040	.170
	Cramer's *V*	.040	.170
N of valid cases		2173	

Age

Figure 3 and Table 6 show data on BMI category by age. There is not a statistically significant difference between BMI categories based on age (p = .147), with a weak association (Cramer's V-.085; Table 7, Table 8).

Figure 3

BMI Category by Age

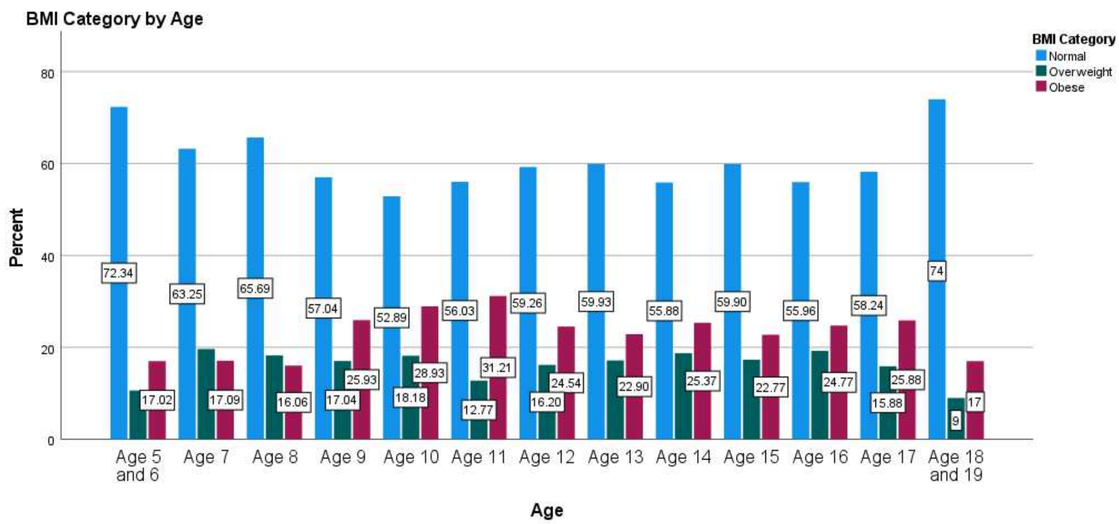


Table 6

Crosstabulation of BMI Category by Age

Variable		BMI category: Normal	Overweight	Obese	Total
Age	5 and 6	34	5	8	47
	7	74	23	20	117
	8	90	25	22	137
	9	77	23	35	135
	10	64	22	35	121
	11	79	18	44	141
	12	128	35	53	216
	13	178	51	68	297
	14	152	51	69	272
	15	121	35	46	202
	16	122	42	54	218
	17	99	27	44	170
	18 and 19	74	9	17	100
Total		1292	366	515	2173

Table 7

Chi-Square Analysis of BMI Category by Age

	Value	*df*	Asymptotic significance (2-sided)
Pearson chi-square	31.253[a]	24	.147
Likelihood ratio	32.442	24	.116
Linear-by-linear association	.487	1	.485
N of valid cases	2173		

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 7.92.

Table 8

Effect Size if Chi-Square Analysis of BMI Category by Age

		Value	Approximate significance
Nominal by nominal	Phi	.120	.147
	Cramer's *V*	.085	.147
N of valid cases		2173	

Race

The following analysis (Figure 4,Table 9) examines BMI category by race. This variable included six groups: Asian, American Indian/Native Alaskan, Black, Native Hawaiian/Other Pacific Islander, White, and Other. For the analysis, I combined Asian, American Indian/Native Alaskan, and Native Hawaiian/Other Pacific Islander. There is not a statistical difference (p = .080) between race and BMI (Cramer's V = .051; Table 10, Table 11). Other had the highest percentage of obese students (31.08) followed by Black (23.88%). The lowest obesity rate was in Asian/American Indian/Native Alaskan/Native Hawaiian/Other Pacific Islander students (20%). Asian/American Indian/Native Alaskan/Native Hawaiian/Other Pacific Islander had the highest percentage of overweight students (20%).

Figure 4

BMI Category by Race

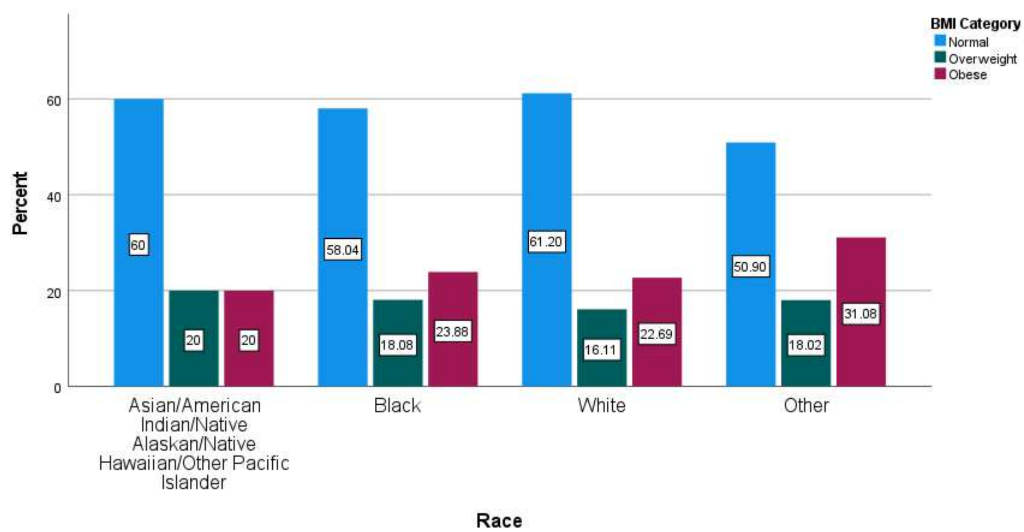


Table 9

Crosstabulation of BMI Category by Race

		BMI Category			
		Normal	Overweig ht	Obese	Total
Race	Asian/American Indian/Native Alaskan/Native Hawaiian/Other Pacific Islander	45	15	15	75
	Black	260	81	107	448
	White	874	230	324	1428
	Other	113	40	69	222
Total		1292	366	515	2173

Table 10

Chi-Square Analysis of BMI Category by Race

	Value	*df*	Asymptotic significance (2-sided)
Pearson chi-square	11.274[a]	6	.080
Likelihood ratio	10.951	6	.090
Linear-by-linear association	1.874	1	.171
N of valid cases	2173		

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 12.63.

Table 11

Effect Size of Chi-Square Analysis of BMI Category by Race

		Value	Approximate significance
Nominal by nominal	Phi	.072	.080
	Cramer's *V*	.051	.080
N of valid cases		2173	

Socioeconomic Status

The final univariate analysis was used to compare BMI categories based on socioeconomic status as measured by the 2004 percentage of the poverty line (Figure 5). The groups used for this analysis were <=130 percent of poverty line, <=185 percent, <=200 percent, <=300 percent, and >300 percent. There was a moderately sized (Cramer's $V = .103$) difference between BMI based on socioeconomic status ($p < .001$; Table 12, Table 13). The lowest poverty category, <=130 poverty line had the most obese students (29.81%) with a decrease in obese students as the percent of poverty line increased (>300 = 15.14%).

Figure 5

BMI Category by Poverty

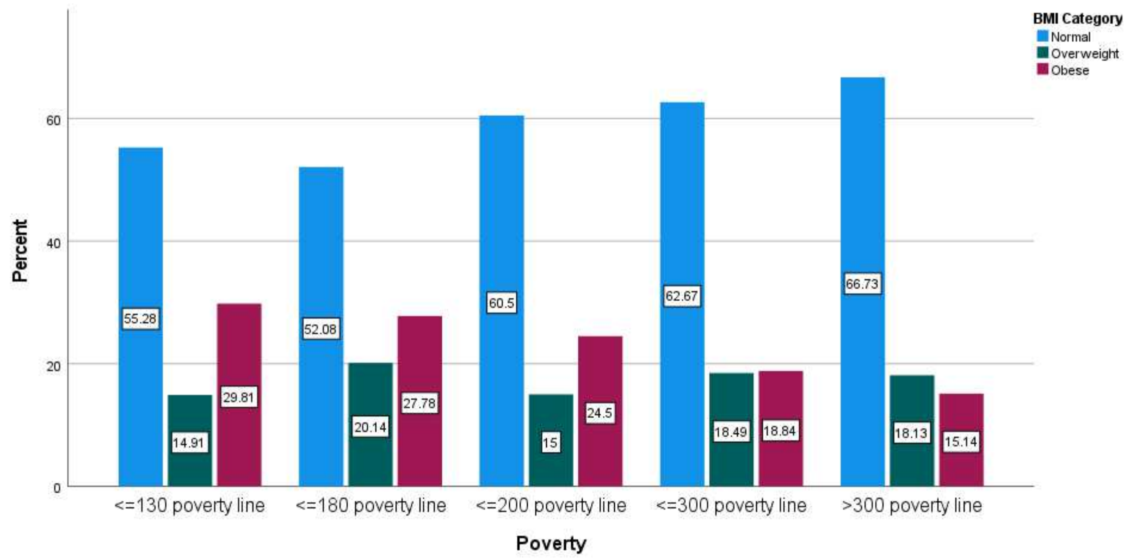


Table 12

Crosstabulation of BMI Category by Poverty

		BMI category			
Variable		Normal	Overweight	Obese	Total
Poverty	<=130 poverty line	382	103	206	691
	<=180 poverty line	150	58	80	288
	<=200 poverty line	242	60	98	400
	<=300 poverty line	183	54	55	292
	>300 poverty line	335	91	76	502
Total		1292	366	515	2173

Table 13

Chi-Square Analysis of BMI Category by Poverty

	Value	*df*	Asymptotic significance (2-sided)
Pearson chi-square	46.335[a]	8	<.001
Likelihood ratio	47.862	8	<.001
Linear-by-linear association	34.376	1	<.001
N of valid cases	2173		

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 48.51.

Table 14

Effect Size of Chi-Square Analysis of BMI Category by Poverty

		Value	Approximate significance
Nominal by nominal	Phi	.146	<.001
	Cramer's *V*	.103	<.001
N of valid cases		2173	

These univariate analyses and chi-square tests showed that the covariates with a statistically significant difference among BMI were race and socioeconomic status. From the literature, all covariates have shown an impact on childhood obesity, so all covariates were used in the analyses.

Results

Descriptive Statistics

The sample population included 2,173 students from across the United States. Of these, 1083 (49.8%) of respondents were male, and 1090 (50.2%) of the respondents were female (Figure 6). Figure 7 shows that the sample was representative of all ages 5-19, with most respondents between the ages of 12 and 16. The bulk of respondents were White, 1428 (65.7%), with 448 (20.6%) Black, 222 (10.2%) Other, 50 (2.3%) responded Asian, 18 (0.8%) American Indian/Native Alaskan, and 7 (0.3%) Native Hawaiian/Other Pacific Islander. Figure 9 shows that the greatest number of students were under or equal to 130 percent of the poverty line (691, 31.8%) followed by those above 300 percent (502, 23.1%). Most student responders were of normal weight (1292, 59.5%) with 366 (16.8%) being overweight, and 515 (23.7%) being obese (Figure 10).

Figure 6

Sample Distribution by Gender

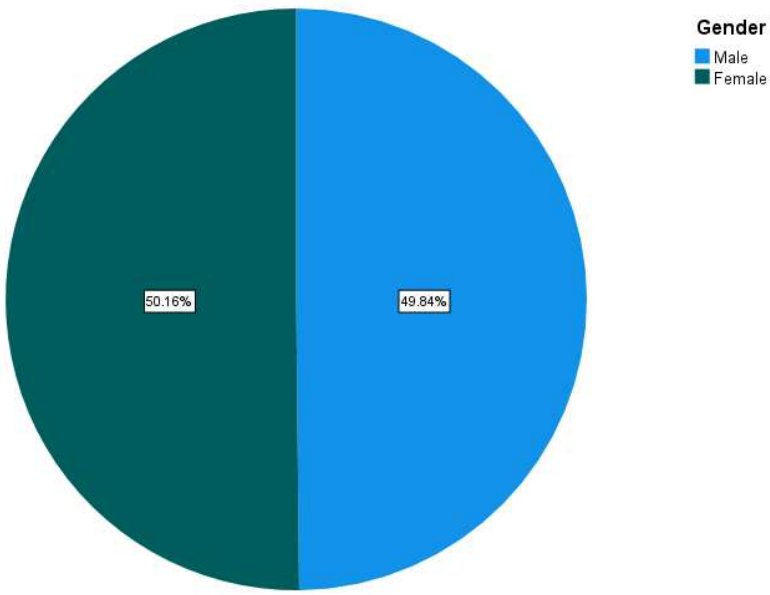


Figure 7

Sample Distribution by Age

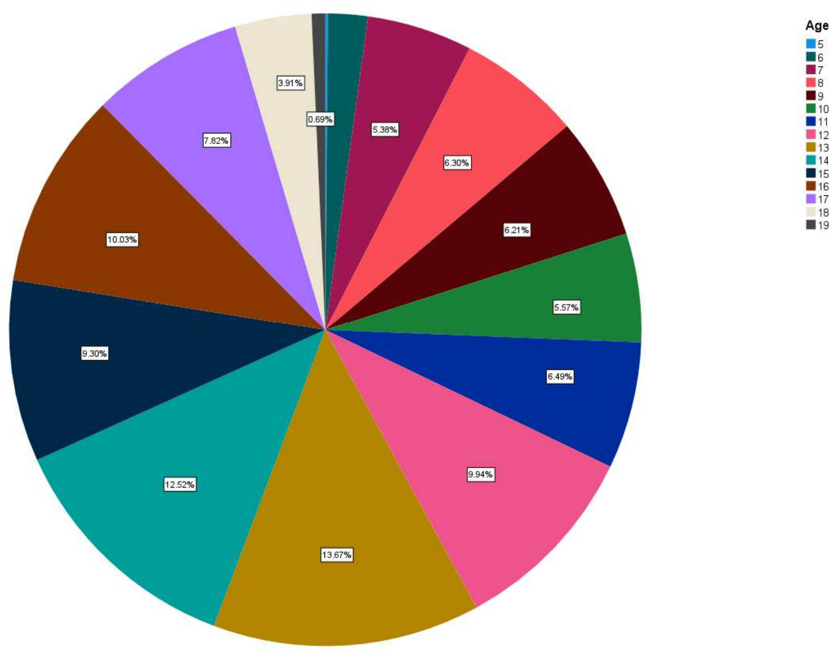


Figure 8

Sample Distribution by Race

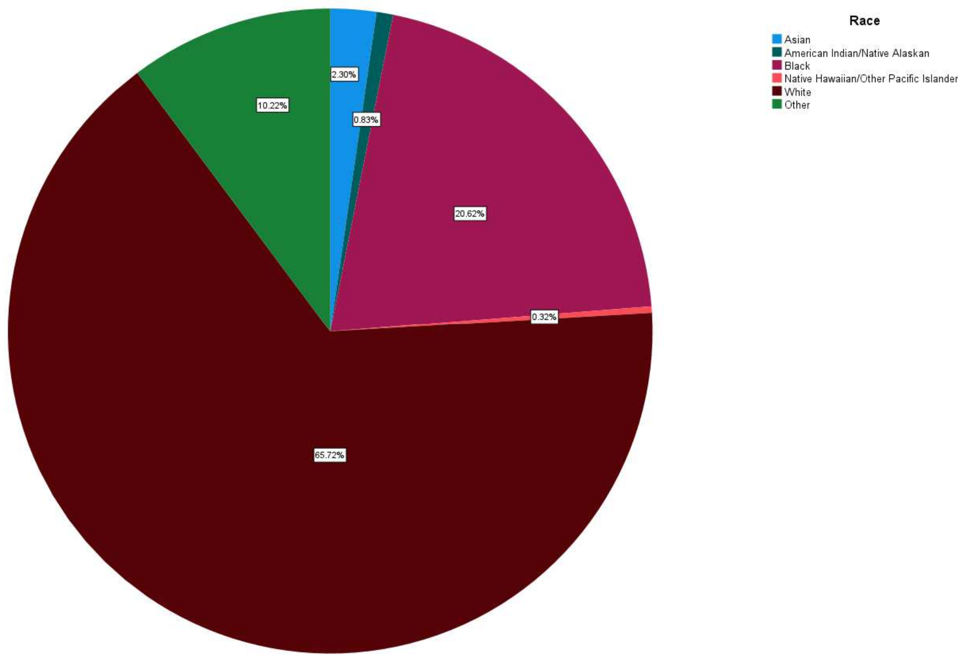


Figure 9

Sample Distribution by Poverty

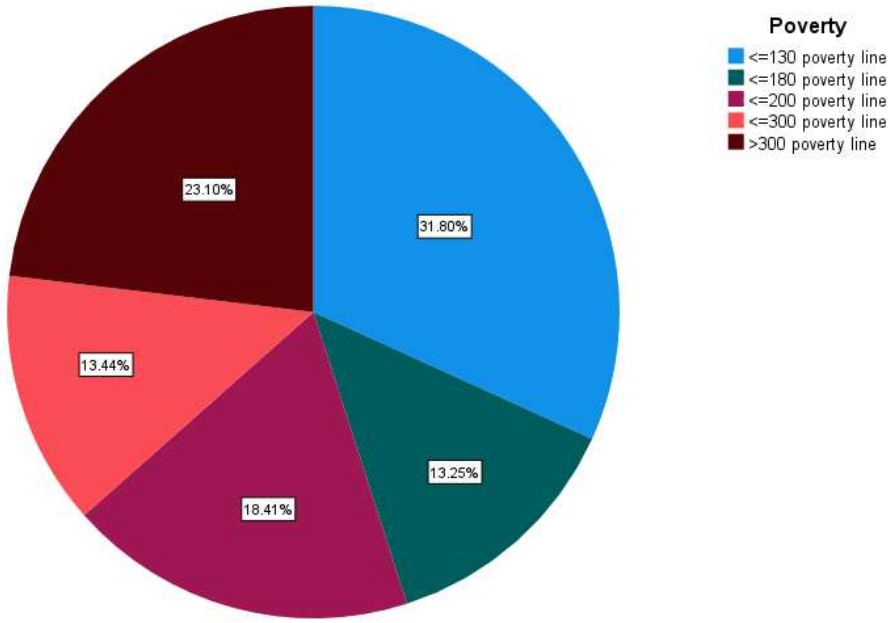
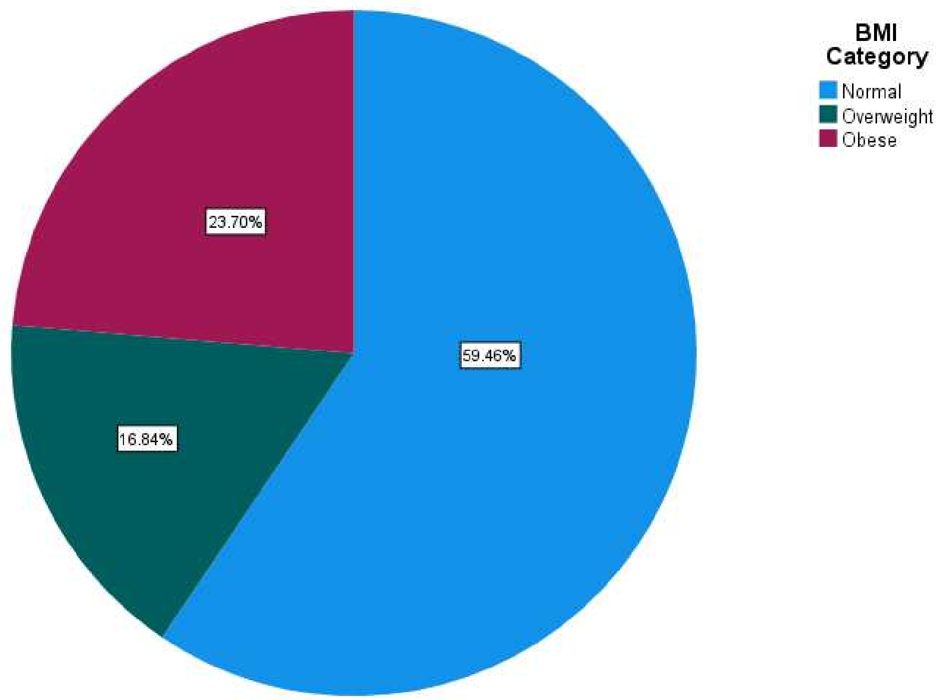


Figure 10

Sample Distribution by BMI Category



Evaluation of Statistical Assumptions

Before running the multinomial logistic regression, I confirmed that the research variables and data fit the multinomial logistic regression and met the following assumptions: dependent variable measured at the nominal level, independent variables are continuous or nominal, independence of observations with mutually exclusive and exhaustive categories in the dependent variable, no multicollinearity, linear relationship between continuous independent variables and the logit transformation of the dependent variable, and there are no outliers (Laerd Statistics, 2018).

Dependent Variable

The dependent variable BMI category fit the multinomial logistic regression assumptions. It was nominal with three categories: 1 = normal, 2 = overweight, and 3 = obese. This dependent variable was used for both RQs.

Independent Variables

Each independent variable included in the multinomial logistic regression must be a continuous or nominal level of measurement. The covariates included in both RQs include gender (nominal), age (continuous), race (nominal), and socioeconomic status (nominal). The independent variable of time of lunch for RQ1 is continuous, but was also recoded to nominal, while the independent variable of perception of time of lunch is nominal. This met the assumptions and fit the chosen analysis.

Independence of Observations

Independence of observations assumes that the included variables and observations are mutually exclusive and exhaustive (Laerd Statistics, 2018). There are no relationships between variables or their values. Those who are obese cannot be included in the group of normal BMI or overweight. This is true for each IV and DV. Consequently, the assumption of independence of observations has been met.

Sample Size

Starkweather and Moske (2011) indicated that sample size guidelines for multinomial logistic regression indicate a minimum of 10 cases per independent variable. This data set has six IVs, so the sample size should be 60 at a minimum. This data set includes 2173 respondents and meets the assumption for sample size.

Statistical Findings

This subsection will include my statistical findings for each RQ. Findings include precise statistics, associated probability values, confidence intervals, effect sizes, and associated statistical output.

Research Question 1

RQ1: Is there a significant association between the time school lunches are served and student BMI when controlling for age, gender, race, and socioeconomic status?

$H_0$1: There is no significant association between the time school lunches are served and student BMI when controlling for age, gender, race, and socioeconomic status.

H_A1: There is a significant association between the time school lunches are served and student BMI when controlling for age, gender, race, and socioeconomic status.

Table 15 shows the Model Fitting Information which compares the full model against a null. The full model includes the independent variable of lunch time as well as the covariates of age, race, gender, and socioeconomic status, while the null model includes the intercept alone with no variables added. For RQ1, the final model is a significant improvement in fit over a null model [$\chi^2(12) = 51.542$, $p < .001$]. This statistical significance indicates that the full model represents a significant improvement in fit over the null model.

Table 15

Model Fitting Information of Logistic Regression for RQ1

	Model fitting criteria	Likelihood ratio tests		
Model	-2 log likelihood	Chi-square	*df*	Sig.
Intercept only	2037.692			
Final	1986.150	51.542	12	<.001

Table 16 shows the Goodness of Fit, which is useful for determining whether a model exhibits good fit to the data. The Deviance chi-square indicates that the model does not fit the data well [$\chi^2(1116) = 1234.741$, $p = .007$], whereas the Pearson's chi-square does indicate good fit [$\chi^2(1116) = 1163.568$, $p = .157$. Smyth (2003) explains that the Pearson test is more robust against model mis-specification.

Table 16

Goodness-of-Fit of Logistic Regression for RQ1

	Chi-square	*df*	Sig.
Pearson	1163.568	1116	.157
Deviance	1234.741	1116	.007

The Likelihood Ratio Tests results in Table 17 show the overall contribution of each independent variable to the model. Using the conventional $\alpha = .05$ threshold, the only significant predictor in the model is poverty (p <.001).

Table 17

Likelihood Ratio Tests of Logistic Regression for RQ1

	Model fitting criteria	Likelihood ratio tests		
Effect	-2 log likelihood of reduced model	Chi-square	*df*	Sig.
Intercept	1986.150[a]	.000	0	.
Age	1986.870	.720	2	.698
Gender	1989.669	3.519	2	.172
Race	1990.939	4.788	2	.091
Poverty	2028.967	42.816	2	<.001
Lunch Time Cat	1987.203	1.053	4	.902

Note. The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

a. This reduced model is equivalent to the final model because omitting the effect does not increase the degrees of freedom.

Table 18 provides information comparing each BMI Category against the Reference Category of Normal. For the category of overweight, there were no significant predictors in the model. For the category of obese, race (b = .165, s.e. = .082, p = .043) and poverty (b = -.220, s.e. = .035, p <.001) were both significant predictors in the model. The odds ratio for poverty of .803 indicates that for every one unit increase on poverty, the odds of a student being obese changed by a factor of .799, odds of being obese decreasing as poverty index went up.

Table 18

Parameter Estimates of Logistic Regression for RQ1

								95% Confidence Interval for Exp(B)	
BMI category[a]		*B*	Std. Error	Wald	*df*	Sig.	Exp(B)	Lower Bound	Upper Bound
Overweight	Intercept	-1.608	.494	10.599	1	.001			
	Age	-.003	.019	.020	1	.888	.997	.962	1.034
	Gender	.215	.119	3.272	1	.070	1.240	.982	1.565
	Race	-.023	.093	.064	1	.800	.977	.815	1.171
	Poverty	-.009	.038	.061	1	.805	.991	.919	1.068
	[Lunch Time Cat=1.00]	.087	.349	.062	1	.803	1.091	.551	2.161
	[Lunch Time Cat=2.00]	.161	.296	.297	1	.586	1.175	.658	2.097
	[Lunch Time Cat=3.00]	0[b]	.	.	0	.	.	.	.
Obese	Intercept	-.818	.424	3.732	1	.053			
	Age	.013	.017	.600	1	.438	1.013	.980	1.047
	Gender	-.002	.105	.000	1	.983	.998	.812	1.227
	Race	.165	.082	4.102	1	.043	1.180	1.005	1.384
	Poverty	-.220	.035	39.601	1	<.001	.803	.750	.860
	[Lunch Time Cat=1.00]	-.181	.286	.401	1	.527	.834	.476	1.462
	[Lunch Time Cat=2.00]	-.146	.233	.390	1	.532	.865	.548	1.365
	[Lunch Time Cat=3.00]	0[b]	.	.	0	.	.	.	.

a. The reference category is: Normal.

b. This parameter is set to zero because it is redundant.

Table 19 shows the classification statistics used to determine which group memberships were best predicted by the model. Normal weight was correctly predicted by the model 100% of the time. The model did a particularly poor job of predicting those who were Overweight or Obese (0%).

Table 19

Classification

	Predicted			
Observed	Normal	Overweight	Obese	Percent correct
Normal	1292	0	0	100.0%
Overweight	366	0	0	0.0%
Obese	515	0	0	0.0%
Overall percentage	100.0%	0.0%	0.0%	59.5%

Research Question 2

RQ2: Is there an association between perceived meal timing and student BMI controlling for age, gender, race, and socioeconomic status?

$H_0$2: There is no association between perceived meal timing and student BMI when controlling for age, gender, race, and socioeconomic status.

H_A2: There is an association between perceived meal timing and student BMI when controlling for age, gender, race, and socioeconomic status.

Table 20 shows the Model Fitting Information for RQ2. The final model is a significant improvement in fit over a null model [$\chi^2(12) = 56.951$, $p < .001$]. The full model includes the independent variable of perception of lunch time as well as the covariates of age, race, gender, and socioeconomic status, while the null model includes the intercept alone with no variables added.

Table 20

Model Fitting Information of Logistic Regression for RQ2

	Model fitting criteria	Likelihood ratio tests		
Model	-2 log likelihood	Chi-square	*df*	Sig.
Intercept only	2192.832			
Final	2135.882	56.951	12	<.001

The Goodness of Fit (Table 21) indicates that the model does not fit the data well for either the Pearson's chi-square [$\chi^2(1284) = 1378.928$, $p = .033$] or the Deviance [$\chi^2(1284) = 1417.669$, $p = .003$. A significant lack of fit with either signifies that the model is not a perfect representation of reality.

Table 21

Goodness-of-Fit of Logistic Regression for RQ2

	Chi-square	*df*	Sig.
Pearson	1339.505	1246	.033
Deviance	1384.882	1246	.003

The Likelihood Ratio Tests (Table 22) show that the only significant predictor in the model is poverty ($p < .001$).

Table 22

Likelihood Ratio Tests of Logistic Regression for RQ2

	Model fitting criteria	Likelihood ratio tests		
Effect	-2 log likelihood of reduced model	Chi-square	*df*	Sig.
Intercept	2135.882[a]	.000	0	.
Age	2136.609	.727	2	.695
Gender	2139.398	3.516	2	.172
Race	2140.509	4.627	2	.099
Poverty	2179.459	43.577	2	<.001
Time of lunch period	2142.343	6.461	4	.167

Note. The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

a. This reduced model is equivalent to the final model because omitting the effect does not increase the degrees of freedom.

Table 23 compares each BMI Category against the Reference Category of Normal. For Overweight, there were no significant predictors in the model. For the category of Obese, race (b = .163, s.e. = .082, $p = .046$) and poverty (b = -.222, s.e. = .035, $p < .001$) were both significant predictors in the model. The odds ratio for poverty of .801 indicates that for every one unit increase in poverty, the odds of a student being obese changed by a factor of .801, odds of being obese decreasing as poverty index went up.

Table 23

Parameter Estimates of Logistic Regression for RQ2

BMI category[a]		*B*	Std. Error	Wald	*df*	Sig.	Exp(B)	95% Confidence Interval for Exp(B) Lower Bound	Upper Bound
Overweight	Intercept	-1.453	.403	12.972	1	<.001			
	Age	-.003	.019	.030	1	.861	.997	.961	1.034
	Gender	.215	.119	3.283	1	.070	1.240	.983	1.566
	Race	-.022	.093	.058	1	.810	.978	.816	1.172
	Poverty	-.009	.038	.058	1	.810	.991	.919	1.068
	[Time of lunch period=1]	-.093	.219	.180	1	.671	.911	.593	1.401
	[Time of lunch period=2]	.022	.181	.014	1	.905	1.022	.717	1.456
	[Time of lunch period=3]	0[b]	.	.	0	.	.	.	.
Obese	Intercept	-.933	.360	6.726	1	.010			
	Age	.013	.017	.585	1	.444	1.013	.980	1.047
	Gender	-.001	.105	.000	1	.994	.999	.813	1.229
	Race	.163	.082	3.980	1	.046	1.177	1.003	1.382
	Poverty	-.222	.035	40.269	1	<.001	.801	.748	.858
	[Time of lunch period=1]	.206	.178	1.334	1	.248	1.228	.867	1.741
	[Time of lunch period=2]	-.334	.180	3.430	1	.064	.716	.503	1.020
	[Time of lunch period=3]	0[b]	.	.	0	.	.	.	.

a. The reference category is: Normal.

b. This parameter is set to zero because it is redundant.

Summary

The results of this study indicate race and poverty are associated with overweight and obese BMI categories. I cannot conclude that there is enough evidence to suggest an association between school mealtimes and BMI. Likewise, I cannot conclude that there is enough evidence to suggest an association between perceived mealtime and BMI. In Section 4, I explore the interpretation of the findings, limitations, recommendations, and implications for social change.

Section 4: Application of Professional Practice and Implications for Social Change

Introduction

The purpose of this cross-sectional, quantitative study was to examine the associations between school lunchtimes, perceived mealtimes, and student BMI. I conducted several statistical analyses to determine if an association was present between the independent, dependent, and covariates. The results of these analyses were presented in Section 3. This study was necessary to fill the gap in literature on school mealtimes and student BMI. In this section, I discuss my interpretation of the findings, the limitations of the study, my recommendations for further research, and the implications for professional practice towards positive social change.

Summary of Key Findings

I used multinomial logistic regression to test whether school mealtimes and perceived meal timing were related to student BMI when controlling for known factors including age, gender, race, and socioeconomic status. The results indicated that race and socioeconomic status influenced BMI, but school lunch times and how students perceived their lunch time did not.

Interpretation of the Findings

Research Question 1

RQ1: Is there a significant association between the time school lunches are served and student BMI when controlling for age, gender, race, and socioeconomic status?

The literature in Section 1 revealed that there are no mandated school lunch times, but that there is a recommended time frame in which lunch should be served to students, between 10 a.m. and 2 p.m. (NSLP). From the 2,173 students included in this study, only one indicated a lunchtime before 10 a.m. (9:30 a.m.), and two students reported lunch time at 2 p.m. However, 202 students reported having lunch before 11 a.m., with 54 reporting a lunch time after 1 p.m.

I performed multinomial logistic regression to answer RQ1. Using the data from the 2004-2005 SNDA, I discovered that the majority of respondents fell into the normal weight category (59.46%), with 16.84% overweight and 23.7% obese, according to BMI. This is higher than the current prevalence rate of childhood obesity, 19.3% (see Trust for America's Health, 2020). The results did not show any significance for those in the overweight category. The results did show statistical significance for those students in the obese category between race and BMI ($p = 0.043$) and socioeconomic status and BMI ($p < 0.001$). This is in line with the literature that non-Hispanic Blacks and low socioeconomic children have a higher risk of obesity (CDC, 2019; Hemmingsson, 2019). In the obese category, there was no statistical significance between time of lunch before 11 a.m. and BMI ($p = 0.803$), time of lunch from 11 a.m. to 1 p.m. and BMI ($p = 0.586$), age and BMI ($p = 0.888$), or gender and BMI ($p = 0.070$). Therefore, I failed to reject the null hypothesis that there is no association between the time school lunches are served and student BMI, controlling for age, gender, race, and socioeconomic status.

These findings extend knowledge in meal timing and obesity. Previously, no research had been done on school lunch times and childhood obesity. While Goheer et al. (2021), St-Onge et al. (2017), and Ruiz-Lozano et al. (2016) demonstrated a significant relationship between meal timing and obese adults, this cannot be generalized to all populations. Additionally, this study used narrow time frames for lunch periods (before 11 a.m., 11 a.m – 1 p.m., after 1 p.m.), while Garaulet et al. (2013) used much different time periods in their study, which considered early lunch before 3 p.m. and late lunch after 3 p.m.

Research Question 2

RQ2: Is there an association between perceived meal timing and student BMI controlling for age, gender, race, and socioeconomic status?

I also performed a multinomial logistic regression to answer RQ2. Suiraoka et al. (2017) expressed how parents perceive meal timing for their children. Parents believed that children may overeat at a meal if they skip or do not eat much at the previous meal. To date, there have been no studies identifying personal perception of meal timing corresponding to BMI. I looked at perceptions of those students in normal, overweight, and obese categories according to their BMI. The results did not show any significance for those in the normal or overweight category. The results did show statistical significance for those students in the obese category between race and BMI ($p = 0.046$) and socioeconomic status and BMI ($p < 0.001$). In the obese category, there was no statistical significance between perceived time of lunch as too early and BMI ($p = 0.803$), perceived time of lunch as just right and BMI ($p = 0.586$), age and BMI ($p = 0.888$), or gender and BMI ($p = 0.070$). Therefore, I failed to reject the null hypothesis that there is no association between perceived meal timing and student BMI, controlling for age, gender, race, and socioeconomic status.

Interpretation of Findings in the Context of the Social Ecological Model

Childhood obesity is a complex and multifaceted health crisis with many causes. Due to these various layers, I chose to base this research in the SEM. As there is no single cause of childhood obesity, the SEM offers levels in which known obesity risk factors may fall. The independent variables and covariates included in this study addressed several of these levels. Age, race, and gender fit the individual level, poverty status fits the interpersonal level, and lunchtimes fits the organizational level. In this study, I found significant findings for particular interpersonal level factors, but not organizational factors. The results of this study indicated that the interpersonal level factors of race and socioeconomic status were associated with childhood obesity. The results of this study also indicated that mealtimes, an organizational level factor, were not associated with childhood obesity. This study furthers the theory that there is no single variable or SEM level that can predict childhood obesity but that influences from each level must be accounted for to prevent childhood obesity.

Limitations of the Study

There are multiple limitations that must be considered from this study. The first limitation of this study was the use of secondary data. Secondary data can affect the reliability of a study due to several limitations, such as missing and unusual values that could affect statistical power, sample size, effect size, and confidence interval (Creswell, 2014). Given that this was a cross-sectional study using a secondary data set, the findings were limited to the variables available. Limitations of cross-sectional studies also include the inability to assess incidence or make causal inference (Wang & Cheng, 2020). The

SNDA-III data were collected from a single year and were survey-based, and the responses were dependent on child/parent reporting. There is also concern that certain groups of students were overrepresented, while others were severely underrepresented. The SNDA-III was collected in the years 2004-2005, demonstrating another limitation. More recent data would be desirable to reflect the most current situation.

While I used the largest and most representative sample available for the research, the population was limited to students in public schools in the United States. The exclusion of children who do not attend public school limits the ability to generalize the findings to all children residing in the United States.

Another limitation of this study is that not all levels of the SEM were operationalized. Future studies should contain variables from all levels of the SEM.

Recommendations

In this study, I aimed to add to the current literature surrounding meal timing and obesity, specifically school mealtimes and childhood obesity. Additional research is warranted to further explore meal timing and childhood obesity at all levels of the ecological frameworks. Future studies should include variables at the community and systems levels of the SEM. To address childhood obesity at the epidemic level that it has reached, higher levels of structures, policies, and systems must be attended to.

In this study, meal timing and perceived meal timing were not associated with increase in BMI; therefore, I recommend that future studies explore additional school mealtime variables, such as breakfast times, recess before lunch, eating lunches in the classroom, and snack offerings, to better understand the facilitators and barriers of school meal timing and childhood BMI. As up to 58% of a student's daily calorie intake is provided by school meals (Cullen & Chen, 2016), more research into the school meal environment is warranted. This study used cross-sectional data, meaning data were taken only at one point in time. As school lunch times may change for students from year to year, cohort data, following students over several years, may provide more statistically significant results.

While meal timing in school may not have a significant association with childhood obesity, there are school practices that may be associated with meal timing. Meal timing data could expand upon Albert et al. (2015), Mathieu et al. (2018), and Chapman et al. (2017), looking at energy balances for students in relationship to recess timing. Likewise, school mealtimes research could further the findings of Green et al. (2019) on classroom behavior and readiness to concentrate after lunch. Additional research on recess behavior, nurses' office visits, and school performance could benefit by comparison to school mealtimes.

Implications for Professional Practice and Social Change

In this study, I examined associations between school lunch times and student BMI. While the results were not significant, future studies on meal timing and childhood obesity could potentially reduce the prevalence and epidemic of obesity.

Professional Practice

The theoretical implications of mealtimes and obesity are not well specified. The findings of this study further add to the body of knowledge on the multifaceted issue of childhood obesity. As obesity trends continue to rise across the United States (CDC, 2021a), public health professionals are in a solid position to further investigate the root causes of childhood obesity, with an emphasis on schools and school lunch practices. Moving forward, it will be important to gather more up-to-date data to gain additional insights into the ways school lunch practices interact and influence childhood obesity. It will also be important to study a cohort of students over time to examine school lunch times for these students over the years, and the impact this has on their body weight.

Positive Social Change

Having a better understanding of how meal timing affects childhood obesity can lead to positive social change. Recognizing the factors and developing interventions to address those factors can better help parents, school officials, and policy makers to make better-informed decisions when creating or modifying policies around when lunch is served.

Conclusion

The purpose of this cross-sectional, quantitative study was to examine the associations between school lunchtimes and childhood obesity. Two RQs were presented to understand the associations under investigation. Multinomial logistic regression analysis results showed that there were no significant associations between school lunchtimes and childhood obesity. However, in line with the literature (see Hemmingsson, 2018; Williams et al., 2018), the only significant association for this study population were socioeconomic status and obesity. The results of the study add to the knowledge of childhood obesity and can be useful to inform and expand efforts toward reduction and prevention of childhood obesity. Future studies should explore additional variables such as breakfast, dinner, and snack times to fully understand the impact meal timing has on childhood obesity.

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