Describing Regional Trends in Childhood Obesity Indicators from 2007 – 2017 with Youth Risk Behavior Survey Data

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Abstract

Obesity is endemic in the United States among adults and children. Behavioral risk factors for developing obesity are well documented, as well as the long-term health impacts observed from becoming obese during childhood. These impacts can permeate into adulthood even if positive changes to an individual's weight status are achieved, making this issue one of great public health importance. An effort to better understanding this public health problem in children has come from the Youth Risk Behavior Survey (YRBS). Administered by the Centers for Disease Control and Prevention every two years, this survey includes questions to gather data on the risk-taking behaviors of children, including those related to obesity development. Prevalence of obesity within the United States varies depending on the geographic location examined, and this study utilizes data from the YRBS to elicit differences in associations of risk factors of respondents and their body mass indexes between the four regions of the United States.

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Preface

I would like to dedicate this work to my parents, the amazing professors on my committee, Hannah Spiegel, and especially my advisor Dr. Christina Mair for her continued support in my journey through the program. Thank you all.

1.0 Introduction

Over the last 30 years overweight/obesity (obesity) has evolved to become endemic among the United States (US) population [1]. In 2016, it was reported that 39.8 percent (93.3 million) of adults and 18.5 percent (13.7 million) of children in the US were considered overweight or obese [2, 3]. These numbers indicate that the US is far behind reaching the Centers for Disease Control and Prevention (CDC) Healthy People goal of less than 30.5 percent of adults and 14.5 percent of children to be overweight/obese by 2020 [4].

The prevalence of children who are obese in the US has plateaued since 2005, meaning that no statistically significant increases have occurred [5]. Regardless, there has been a net increase in childhood obesity prevalence during the last decade from 16.8 percent in 2008 to 18.5 percent in 2016 [6]. From a life-course perspective, the Health Belief model suggests that behaviors contributing to obesity in children can be targeted and modified in order to carry obesity-preventing behaviors over a person's life [7].

Obesity is a complex public health issue with a variety of contributing factors [8]. The origins of obesity are set in individual, relationship, community, and society-based frames [9-12]. This multi-framed approach represents an important step in creating lasting behavioral changes in those with or at highest risk for obesity [13]. With such a diverse range of contributing elements, some research has used a social-ecological approach to better understand how these factors may interact and shape the overall public health problem of obesity [14]. The goal of this research is to understand the ways in which these frames impact rates of childhood obesity specifically by uncovering how behavioral factors pertaining to physical activity, diet, and mental health are contributing to childhood obesity among the four regions of the US over a ten-year period.

1.1 Theoretical Basis: The Social-Ecological Model

The social-ecological model has been endorsed by the Institute of Medicine as well as the World Health Organization as a foundation for creating interventions and policies that aim to prevent and reduce childhood obesity prevalence [15, 16]. A depiction of the social-ecological model is represented below.

Figure 1: Social-Ecological Model Visual Representation

The model shows how multiple levels of socially organized systems are contained within each other to form the environment in which an individual lives [17]. In terms of obesity, risk factors exist on each level and contribute in different ways to the problem. The individual level directly influences the next level above (relationship), and indirectly affects the other, superior, levels. Societal-level factors permeate aspects of each layer within it.

Individual-level factors are those related to a person's biology and personal history, such as age, socioeconomic status, and substance use. For example, lower family income has been shown to increase a child's risk for developing obesity [18]. In addition, tobacco use among children in the form of cigarettes or vaping is associated with increased risk for obesity [19]. Other individual factors contributing to the problem include those related to self-perceived body image, knowledge about nutrition, and attitudes towards healthy foods such the perceived benefits of eating healthy [20].

Relationship-level factors include aspects of the home environment such as feeding practices, parental weight status, and parenting style. In terms of feeding practices, different approaches to how parents restrict, monitor, or 'force' their children to eat specific types of food has been shown to be a potential predictor in risk for developing obesity [21]. An adult's approach to parenting can influence a child's risk for developing obesity as a recent meta-analysis by Want et al. showed children with obese parents are more than two times as likely to become obese compared to children of normal-weight parents [22].

A community can be defined in a variety of ways. It can have cultural boundaries, social boundaries, or geographic boundaries set by state or country lines. For this study, community lines are defined as the four separate regions of the US as set by the CDC. Factors that have community-level influence can include those related to the built environment. The built environment refers to the human-made space in which a person or group of people live out their daily life, and can have a major impact on their overall health [23]. An example of this is the walkable food environment within a community. Having access to healthy food options within walking distance can lower the odds of a child developing obesity [24]. When the community environment is deprived of resources seen in more affluent areas such as grocery stores, community centers, libraries, and safe spaces for children to be active, higher Body Mass Index (BMI) values are observed at earlier ages with faster rates of increase compared to children in underserved communities [25]. Other community-level factors include elements of the school environment such as annual vital measurements and nutritional services like the National School Lunch program.

Societal-level factors include governmental policies, laws, and cultural norms. These factors influence how, where, and when activities of daily life are carried out as well as how people generally view them. One societal-level factor implemented by the government to help reduce obesity rates would be a policy that taxes items known to increase risk of obesity such as fast foods or sugary drinks. A study out of Germany using population modeling recently found that a 20 percent tax on sugar-sweetened beverages could reduce the consumption of such beverages and ultimately help reduce obesity prevalence [26]. Policies such as this, as well as others that increase access to grocery stores within communities, support food assistance programs and prices, and improve the built environment can all contribute to reduction in obesity risk factors [27].

1.2 Public Health Importance of Childhood Obesity

Obesity during childhood can result in negative, downstream health outcomes in adulthood. These conditions include cardiovascular disease, type 2 diabetes, insulin resistance, sleep apnea, asthma, cancer, polycystic ovarian syndrome, and infertility

[28]. In addition, being overweight in childhood increases risk of mortality from cardiovascular and cerebrovascular disease, and colorectal and breast cancers. These elevated risks persist even if an individual attains a healthy weight upon reaching adulthood, reinforcing the importance for better understanding how to approach prevention of obesity in childhood [29].

A key development time in a child's life occurs in the school setting [30]. Children in middle school who are overweight tend to receive more detentions, be late to school or miss school days more often, and participate less in afterschool activities than their normal-weight counterparts, which leads to decreased scholastic achievement [31]. These impairments in the classroom can have compounding effects on the pressures and stereotypes faced by overweight children in school and can impact their mental health. High weight has been shown to be associated with lower social quality of life in school settings than normal weight status [32]. Stereotypes such as being unhealthy, lazy, unhygienic, and socially inept are attached to some of these children and negatively contribute to their perceived abilities to counteract the effects of being overweight; they are also less likely to discuss their feelings and make them known to those who may be able to help [33]. Mental, behavioral, or developmental disorders (MBDDs), including body image disorders, eating disorders, self-esteem problems, depression, and suicidal ideations, are more likely to develop due to a child's weight status [34]. MBDDs affect one in every five children in the US and are estimated to result in $247 billion in healthcare costs each year due to increased health service utilization [35].

1.3 Regional Differences in Obesity

The prevalence of obesity throughout the US varies from state to state and between groups of states (regions). The US consists of four regions: Northeast, Midwest, South, and West (see Appendix A for composition of regions and map). The southern US has the highest rates of adult obesity, with Texas, Louisiana, Mississippi, and West Virginia holding the highest prevalences at 33.0, 36.2, 37.3, and 38.1 percent respectively [36]. In the Midwest, Iowa has the highest prevalence of obesity at 36.4 percent. States in the Northeastern and Western US have markedly lower overall obesity prevalences, with an average range of 25 to 30 percent compared to 30 to 35 percent and greater than 35 percent in the Midwest and South respectively. The same regional trends are present for childhood obesity. The Southern US is composed of states with the highest prevalence of childhood obesity with Texas, Louisiana, Mississippi, Oklahoma, and Arkansas at 18.6, 17.0, 18.9, 17.1, and 21.7 percent obesity respectively.

Differences exist in the incidence and prevalence of acute and chronic conditions related to obesity across states and regions of the US. There is a region of the US where specific obesity-related health outcomes such as mortality from stroke are more common in adults than elsewhere, and it is often referred to as the Stroke Belt [37]. The Stroke Belt is a region of the southeastern US (Alabama, Arkansas, Georgia, Indiana, Kentucky, Louisiana, Mississippi, Tennessee, North Carolina, South Carolina, and Virginia) where mortality from stroke is significantly higher per 100,000 adults than the rest of the country. Specifically, out of the 140,000 people in the US who die from stroke each year, the majority occur in this region [38]. Additionally, the Stroke Belt has a higher prevalence of heart disease than other areas of the US [39]. As the leading cause of death in adult men and women in the US, heart disease poses a major threat to the quality of life of those living in this region. Furthermore, prevalence of Type-2 Diabetes is estimated to be more common in the Southern region of the US [40].

The differences in adult disease prevalence by region of the US suggests potential differences in how strongly similar factors are contributing to obesity and related conditions within those regions. An upstream approach to understanding this problem suggests that these differences may have roots in health behaviors that are a result of cultural norms or the resources most readily available to people within specific regions. For instance, more fast food is consumed in the South compared to other regions of the US [41]. Additionally, children in low-income families are more likely to be obese regardless of race, and poverty is associated with a higher average BMI [42]. Furthermore, the Southern US has the highest poverty rate (13.6 percent) compared to others (North 10.3 percent, Midwest 10.4 percent, West 11.2 percent) [43].

1.4 Protective and Risk Factors for Obesity

Physical activity has a well-established role in prevention of obesity in adults and children [44, 45]. Creating a desire to be physically active in children can result in lasting behavior change that can give them the power to maintain a healthy weight status throughout their life course [46]. The American Heart Association recommends 60 minutes of physical activity each day of the week for children ages 6-17 years of age [47]. A barrier today for children to achieve this standard is high screen media exposure and consequent sedentary behavior. Sedentary behavior has been established as a cause of negative health consequences in a dose-response fashion; and more than two hours of screen time per day decreases self-esteem, pro-social behavior, and academic achievement [48].

Diet represents another major contributor to childhood obesity in the US [49]. The US Department of Agriculture has set specific recommendations for a healthy diet and notes that American children and adults do not consume the daily recommended servings of fruits and vegetables, as well as consuming too many sugary beverages [50]. These unhealthy eating habits become exacerbated with increases in screen media exposure, as well as increased exposure to marketing of high-calorie and low-nutrient food and beverages [51]. As consumption of fruit and vegetables represents a main component of achieving a healthy diet, seeing how children's eating habits around these can provide insight into their current and future BMI [52].

Mental health issues in children are defined as serious changes in the way they behave, learn, or handle their emotions, causing distress and problems throughout the day [53]. A child's mental health can affect their ability to create or maintain behaviors that are consistent with a healthy lifestyle. For instance, depression in children may increase the likelihood of adopting behaviors such as unhealthy eating, sedentary behavior, and sleeping problems [54]. These behaviors increase the risk of developing obesity, and if left unchanged may make children more likely to be obese in adulthood [55]. In addition, obesity alone has been shown to be a risk factor for developing depression in children and adolescents [56]. This bi-directional association suggests that each can be a risk factor for the other and reinforces the need for better understanding prevention measures; however, a state of duality between functional health and BMI exist in a disproportionate state.

This duality is the obesity paradox – where having a greater BMI is associated with lower mortality rates for certain chronic health outcomes such as kidney disease, heart failure, and obstructive pulmonary disease compared to individuals of healthy BMI – indicates that obesity is not always associated with years of life lost [57]. This may be a direct result of the inability of BMI to truly represent body fat composition in an individual, but the overall mechanism of this protective effect remains unknown [58]. However, as the obesity paradox relates only to a reduction in mortality from these health outcomes, obesity still contributes to the development of these conditions.

1.5 Economic Impact of Obesity

In 2014 adult obesity resulted in an estimated cost of two trillion dollars worldwide, making up 2.8 percent of the global gross domestic product [59]. The most recent estimate of the financial burden of obesity in the US was $147 billion in 2008 [60]. Given an average inflation rate of 1.63 percent per year of the US dollar between 2008 and 2019, and assuming obesity spending has remained constant, the total annual cost of obesity today could be over $175 billion [61].

The total cost of obesity stems from both direct and indirect costs. Direct costs represent resources consumed as a result of providing a healthcare service, such as the labor required to perform such services. Some examples of direct medical costs include prescription medication, use of primary care facilities, and utilization of specialists for treatment of comorbid conditions. For example, obese adults were found to spend $726 more than their non-obese counterparts on healthcare annually after adjusting for disabilities and other demographic characteristics [62].

Indirect costs of obesity are losses of economic production related to an illness. Presenteeism, absenteeism, disability, and premature mortality are all common indirect costs of obesity [63]. Presenteeism in this instance refers to obese employees being unable to perform at full productivity as often as normal-weight counterparts, often as a result of working through an illness related to their weight status [64]. Absenteeism is exhibited in a greater number of sick days taken on average than those of non-obese BMI [65]. Disability is similar to absenteeism but differs in that the time spent away from work involved a disability claim to an insurance provider. Premature mortality is higher in obese individuals, meaning all-cause and cause-specific mortality is higher and occurs sooner compared to normal weight individuals [66]. These indirect productivity and mortality issues represent a major contributor to the overall economic impact of obesity, contributing over 50 percent of the total cost to health [67].

The overall evidence on cost effectiveness of interventions aiming to treat and/or prevent childhood obesity lacks generalizability [68]. This is mainly a result of the heterogeneity of research approaches used to investigate childhood obesity [69]. However, Finkelstein et al. reported that if obesity incidence were to remain at 2010 levels, the US healthcare system would save $549.5 billion over a 20-year period [70]. The model used in this projection shows how an effort to create programs, policies, and interventions to target obesity can potentially save a significant amount in health care costs. Therefore, in order for an intervention to be optimized for reducing health care costs, changes on multiple levels of the socio-ecological model must be achieved in concert with one another [71].

1.6 Obesity Interventions

Modifying health behaviors requires a sensitive approach to elicit positive changes. Nobody enjoys being told how they should live their life – what you should and should not eat, what you should do with your free time, or what makes you happy despite a particular cost. With such a variety of determinants contributing to obesity, it is unsurprising that the focus of childhood obesity preventive interventions are wide-ranging and display various levels of success [72]. Obesity-targeted interventions can focus on one level or multiple levels of the social-ecological model [73].

The National Physical Activity Plan is a non-profit organization created in 2016 to increase the number of Americans who are physically active. In cooperation with US policy makers, and with the socio-ecological model as its main theoretical foundation, it has set guidelines for creating interventions, surveillance systems, and reporting out standards for organizations attempting to tackle this public health problem [74]. This evidenced-based approach to reduce sedentary behavior amongst Americans has not been evaluated for any potential impacts on BMI.

Analyses of individual studies in the literature are internally valid; however, the generalizability of study findings is often limited. A focus on weight status as the main outcome measure permeates the literature, despite the fact that newer evidence points to positive behavior change as a more reliable measure for long-term obesity prevention

[69, 75-77]. Changes in behavior, such as building belief in the value of eating fruits and vegetables or creating a desire to participate in a sport, are usually achieved by modifying initial beliefs towards the value of diet, exercise, and sedentary behaviors on one's overall health.

Ideally, programs aim to create a lasting sense of empowerment in a child that maintaining these specific behaviors will benefit their quality of life. Achieving these behavior changes are often difficult despite the effectiveness of an intervention or program. For example, interventions targeting adolescent diet can be difficult due to cost of healthy food options or consistency from parents to enforce a healthy diet [78]. Many interventions see their effectiveness improve with parental buy-in, and without a positive parent-child relationship its efficacy can decrease [79].

Many obesity-related interventions aim to reach a large target population, and with 70 percent of Americans having access to smartphones or tablets, electronic interventions in the form of applications (aps) have become popular [80]. Developing an ap that is effective and engaging can be challenging; however, they have been shown to be effective educational tools to assist in eliciting positive behavior changes when supplementing health-promotion interventions in a primary care setting [81]. When examined independently, aps have been found to have various degrees of success compared to their in-person intervention counterparts. The best results of aps were obtained when they were paired with a physical intervention and included multiple behavior change techniques [82].

Effective public health interventions that target childhood obesity often achieve greatest impact when multiple levels of the social-ecological model are targeted [83]. As behaviors are enforced on multiple levels, retention is likely to increase [84]. In other words, if a child has behavior changes reinforced at home, in their community, and at school, they are more likely to be retained. This requires buy-in from parents, members of a community, and school staff, and can be additionally reinforced by changes in societal perspectives towards diet, exercise, mental health, and other targets of these programs that contribute to obesity.

A regional program out of Maine and the Barbara Bush Foundation called Let's Go! utilized regional workgroups to achieve healthier lunches in over 70 schools in the Northeastern US [85]. A program aiming to prevent childhood obesity in Massachusetts utilized primary care settings to engage parents and shift social norms in the region about the value of a healthy lifestyle through coaching, and achieved family centered changes in weight status [86].

2.0 Primary Research Question and Hypotheses

The health belief model states that a personal threat of a disease or illness combined with that person's trust in a recommended behavior change to combat such outcomes will predict their likelihood of adopting that change. The present study attempts to uncover how behavioral factors pertaining to physical activity, dietary fruit and vegetable consumption (diet), and mental health are contributing to childhood obesity across the four regions of the US over a ten-year period. The primary research question was the following: Are measures of diet, exercise, and the mental health of 12-17 year olds associated with BMI in each of the four regions of the US from 2007 to 2017?

<u>Hypothesis 1</u>

H_1: Dietary consumption of fruit and vegetables will be inversely related to BMI in all four regions of the US during the sampling period.

H_{01}: There is not a significant inverse relationship between dietary consumption of fruit and vegetables to BMI in all four regions of the US during the sampling period.

<u>Hypothesis 2</u>

H_2: Physical activity will be inversely related to BMI in all four regions of the US during the sampling period.

$H0_2$: There is no significant inverse relationship between physical activity and BMI in all four regions of the US during the sampling period.

<u>Hypothesis 3</u>

H_3: A behavioral variable representing depression will be positively related to BMI in all four regions of the US during the sampling period.

H_{03}: There is no significant relationship between a behavioral variable representing depression and BMI in all four regions of the US during the sampling period.

Hypothesis 4

H_4: The strength of the associations between dietary consumption of fruits and vegetables, physical activity, depression and BMI will vary by region.

H_{04}: There is no variation in the strength of associations between dietary consumption of fruits and vegetables, physical activity, depression and BMI by region.

3.0 Methods

Ten years of publicly available, de-identified Youth Risk Behavior Survey (YRBS) data was downloaded directly from the Centers for Disease Control and Prevention (CDC) webpage. These data were downloaded as a Microsoft Access .dta file and converted into a .exc file using Microsoft Excel. Data were cleaned and imported into Stata v15 for analysis. Linear regression was used to investigate the three hypotheses. Survey weights were applied as per the data-analysis guide provided by the CDC (see link in Appendix B).

3.1 The Youth Risk Behavior Survey

Since 1990, the Youth Risk Behavior Surveillance System (YRBSS) has administered on a biennial basis a survey to participating high schools called the YRBS. The goal of this survey is to elicit knowledge about health risk behaviors related to substance use, sexual health, mental health, diet, and physical activity [87].

The YRBS is a state-based, cross-sectional paper survey distributed by teachers and completed by participating students in their classrooms. This survey is based on a multi-stage cluster design that uses participating schools (public and private) to represent the non-institutionalized, adolescent population. The sampling frame for this survey is participating schools within the US and District of Columbia. The sampling units are individual students participating in the survey within each school. National datasets such as the YRBS that compose of self-reported data have been utilized to measure this public health problem in the past, and have been evaluated for validity [88].

3.2 Study Population

The present study used YRBS survey data from the 50 states and the District of Columbia from 486,376 students between 12 and 17 years of age over a ten-year period (2007-2017). Exclusion criteria included being above the age of 17 and reporting a BMI of below 12 or above 55, as these indicate extreme underweight, morbid obesity, or a respondent/coding error. The four geographic regions of the US – Northeast, Midwest, South, and West – were used to cluster respondent's answers and investigate differences. Samples sizes of the four regions were 150,803, 88,693, 145,016, and 101,864 students for the Northeast, Midwest, South, and West respectively.

3.3 Data Variables

The YRBS contains a variety of questions pertaining to a respondent's diet and physical activity habits, as well as mental status indicators. In order to create a measure that most accurately reflects healthy dietary choices, data from multiple questions of the YRBS were combined. This variable was created utilizing a scoring system similar to that used in a dissertation thesis from Walden University [89]. In that case, answer choices for individual questions were given point values aimed at representing the weekly frequency of consumption of a certain food. For this study, a similar system was used, but here ranges were created to categorize values into groups representing weekly fruit and vegetable consumption. Questions 71, 72, 73, 74, and 75 were used to create this composite variable (see Appendix C for descriptions). Numbers 0 – 6 were used to represent scores of 0-2.99, 3-5.99, 6-8.99, 9-11.99, 12-14.99, 15-17.99, and 18-20 respectively. For correlation analyses, numerical values were used, not the categories.

Question 79 of the YRBS was used to measure the physical activity of respondents. It asked how many days per week a respondent was physically active for at least 60 minutes at a time. In order to better determine if physical activity is a regular behavior exhibited by respondents, the question was dichotomized. This broke up responses into two groups, those who responded five times per week or more, and four times per week or less. Current recommendations state that children should be active at least 60 minutes every day [90]; however, this would have excluded too many respondents and been an inaccurate representation of physical activity in the cohort.

For examining depression, question 25 of the YRBS was used. This was a yes or no question asking, "During the past 12 months, did you ever feel so sad or hopeless almost every day for two weeks or more in a row that you stopped doing some usual activities?" This question most accurately reflected the description of depression in children based on the CDC's definition [91].

Individual respondent data for the YRBS is coded with information regarding which state the survey was completed. The Northeast, Midwest, South, and West states were assigned 1, 2, 3, and 4 respectively for organization, then these geographical regions, as defined by the CDC, were used to create corresponding dummy variables. The year each survey was administered was pre-coded with a 'survey year' dummy variable. This variable represented the chronological order of survey years since the inception of the YRBS (see codebook).

Grade was coded as 1, 2, 3, and 4 for 9th, 10th, 11th, and 12th grades respectively. Age was coded as 1, 2, 3, 4, 5, and 6 to represent 12 years old and younger, 13, 14, 15, 16, and 17 years old respectively. Grade and age were both used in the analysis to account for the fact that children younger than average for their grade may be in 9th grade. Race was broken down into seven different categories. American Indian/Alaskan native, Asian, Black/African American, Hispanic/Latino, Native Hawaiian/Pacific Islander, White, or multiple races (non-Latino) were coded as 1 – 7 respectively. Sex was coded as 0 and 1 for male and female respectively.

3.4 Data Analysis

Microsoft Access and Excel were used to clean data prior to importation into STATA v15.1. Survey data were analyzed using STATA's survey (svy) functions. Weights and survey set parameters were coded using instructions from the YRBS Codebook (see Appendix B for link). Sex, race, grade, and survey year were controlled for in the regression analyses. There were no significant temporal trends in the data apart from the Midwest. Threshold for significance was set at $p < 0.05$ using 95 percent confidence intervals. Multiple linear regression was used to explore relationships of the variables about depression, fruit and vegetable consumption, and exercise to BMI separately in each of the four geographic regions of the US. These regression analyses were performed to investigate how diet, exercise, and depression variables related to BMI of respondents within different regions in the US.

In addition, a linear regression model was run for the entire sample, including region as a dummy variable to see if (1) residence in a given region was associated with BMI and (2) whether associations between diet, exercise, and depression and BMI were different across regions. STATA's interaction and parameter test features were used to investigate if the overall differences across regions were significant. These sets of analyses allowed for the exploration of absolute and relative differences of behavioral variables and their associations to BMI.

4.0 Results

The population was nearly even split between male and female respondents at 51.69 and 48.31 percent respectively. Overall respondent demographics are displayed in Table 1, and these demographics are broken down by region in Table 2.

Table 1: Respondent Demographics from 2007-2017

Variable	n (%)
Sex	
Female	250,115 (51.69)
Male	233,730 (48.31)
Race	
American Indian/Alaska Native	10,209 (2.15)
Asian	21,787 (4.50)
Black or African American	59,250 (12.48)
Hispanic/Latino	83,871 (17.66)
Native Hawaiian/Other Pacific Islander	8,989 (1.89)
White	266,478 (56.12)
Multiple Races (Non-Hispanic)	24,225 (5.10)
Grade	
9th grade	150,837 (31.30)
10th grade	145,693 (30.23)
11th grade	129,153 (26.80)
12th grade	56,219 (11.67)
Age	
12 years old or younger	821 (0.17)
13 years old	2,220 (0.46)
14 years old	66,862 (13.79)
15 years old	142,898 (29.48)
16 years old	145,191 (29.95)
17 years old	126,802 (26.16)
Region	
Northeast	150,803 (31.01)
Midwest	88,693 (18.24)
South	145,016 (29.82)
West	101,864 (20.94)

Table 2: Respondent Survey Data by Region 2007-2017

YRBS Question	Region, n (%)			
Depression	Northeast	Midwest	South	West
Yes	40,276 (27.39)	22,529 (26.92)	40,799 (28.52)	30,470 (30.33)
No	106,755 (72.61)	61,163 (73.08)	102,271 (71.48)	69,995 (69.67)
Physical Activity				
Yes	29,423 (22.03)	21,145 (25.87)	30,780 (24.91)	23,340 (24.45)
No	104,133 (77.97)	60,592 (74.13)	92,777 (75.09)	72,116 (75.55)
Diet				
0	4,375 (15.17)	13,986 (16.90)	22,165 (17.53)	13,315 (16.64)
1	7,359 (25.52)	21,513 (26.00)	33,890 (26.80)	20,421 (25.52)
2	6,220 (21.57)	18,156 (21.94)	27,109 (21.44)	17,478 (21.84)
3	4,211 (14.61)	11,275 (13.63)	16,613 (13.14)	10,885 (13.60)
4	3,047 (10.57)	8,403 (10.16)	12,534 (9.91)	8,092 (10.11)
5	1,707 (5.93)	4,397 (5.31)	6,097 (4.82)	4,397 (5.49)
6	1,912 (6.63)	5,008 (6.06)	8,047 (6.36)	5,443 (6.80)

Table 3 displays the breakdown of each region during the survey period by racial composition. Each region was significantly different from each other by racial makeup. P-values for these differences were all p<0.01. NHOPI represents the Native Hawaiian/Other Pacific Islander classification.

Table 3: Regional Demographics

Race	Region, n (%)			
	Northeast	Midwest	South	West
American Indian/Alaska Native	2,585 (1.77)	1,854 (2.13)	2,232 (1.57)	3,538 (3.56)
Asian	8,282 (5.67)	2,276 (2.61)	3,498 (2.46)	7,731 (7.77)
Black or African American	16,984 (11.63)	9,814 (11.27)	30,197 (21.24)	2,255 (2.27)
Hispanic/Latino	31,548 (21.60)	1,2067 (13.86)	19,362 (13.62)	20,894 (21.00)
NHOPI	1,078 (0.74)	446 (0.51)	861 (0.61)	6,604 (6.64)
White	80,409 (55.05)	56,891 (65.34)	7,8237 (55.03)	50,941 (51.19)
Multiple Races (Non-Hispanic)	5,169 (3.54)	3,718 (4.27)	7,793 (5.48)	7,545 (7.58)

The mean BMI by each region in each of the survey years is displayed in Table 4. The overall BMI mean was greatest for the Southern region of the US, with the West having the lowest mean BMI. No temporal trend in BMI was present during the study period. Regions are all significantly different by BMI each year (p-value <0.01).

Table 4: Mean Regional BMI over Sampling Period

	Region, mean BMI (SE)			
Year	Northeast	Midwest	South	West
2007	23.04 (0.05)	23.09 (0.04)	23.42 (0.04)	22.58 (0.05)
2009	22.99 (0.05)	22.98 (0.04)	22.86 (0.07)	22.56(0.04)
2011	22.85 (0.04)	22.94 (0.04)	23.31 (0.04)	22.73 (0.06)
2013	22.82 (0.04)	22.98 (0.04)	23.22 (0.03)	22.95 (0.06)
2015	23.12 (0.05)	23.23 (0.05)	23.67 (0.04)	23.19 (0.06)
2017	23.18 (0.04)	23.57 (0.05)	23.55 (0.04)	23.32 (0.06)
Overall	23.05 (0.02)	23.13 (0.02)	23.33 (0.02)	22.97 (0.03)

Table 5 displays regression analyses run individually by region to investigate how BMI might be associated with answers to survey questions (behavioral variables) during the study period. These analyses adjust for sex, race, grade, and survey year. Regression coefficients (Coef), standard error (SE), t-score, p-value, and a 95 percent confidence interval (CI) are reported for each region. A p-value displayed of 0.00 should be assumed to be less than 0.01. The Midwest was significant for survey year.

Table 5: Linear Regression of Survey Data to BMI by Region

Region, (n)	Construct	Variable	Coef	SE	T-score	P-value	95% CI	
Northeast, (22,837)								
	Sex	Female	-0.64	0.09	-6.95	0.00	-0.82	-0.46
	Race/Ethnicity	American Indian	0.10	0.49	0.20	0.84	-0.87	1.07
		Asian	-1.35	0.26	-5.19	0.00	-1.86	-0.84
		Black	1.03	0.20	5.22	0.00	0.64	1.42
		Hispanic/Latino	0.92	0.16	5.88	0.00	0.61	1.23
		NHOPI	-0.61	0.55	-1.11	0.27	-1.68	0.47
		Multiple non-Latino	1.15	0.30	3.85	0.00	0.56	1.74
	Grade	Tenth Grade	0.73	0.16	4.66	0.00	0.42	1.03
		Eleventh Grade	1.19	0.12	9.96	0.00	0.96	1.43
		Twelfth Grade	1.35	0.17	7.89	0.00	1.01	1.68
	Year	Survey Year	0.01	0.03	0.46	0.64	-0.04	0.07
	Behavior	Depression	0.67	0.13	5.38	0.00	0.43	0.92
		Physical Activity	-0.64	0.12	-5.18	0.00	-0.88	-0.39
		Fruit/Veg Consumption	-0.03	0.03	-1.02	0.31	-0.09	0.03
		Intercept	22.52	0.14	161.65	0.00	22.25	22.79
Midwest, (70,821)								
	Sex	Female	-0.78	0.05	-16.05	0.00	-0.87	-0.68
	Race/Ethnicity	American Indian	1.02	0.22	4.65	0.00	0.59	1.45
		Asian	-1.07	0.14	-7.52	0.00	-1.35	-0.79
		Black	1.30	0.10	13.51	0.00	1.11	1.49
		Hispanic/Latino	0.92	0.07	12.34	0.00	0.77	1.06
		NHOPI	-0.35	0.24	-1.46	0.14	-0.82	0.12
		Multiple non-Latino	0.64	0.13	4.87	0.00	0.38	0.90

Table 5 Continued

	Grade	Tenth Grade	0.56	0.07	7.58	0.00	0.42	0.71
		Eleventh Grade	1.00	0.06	15.92	0.00	0.88	1.12
		Twelfth Grade	1.16	0.10	11.56	0.00	0.96	1.36
	Year	Survey Year	0.07	0.02	3.48	0.00	0.03	0.11
	Behavior	Depression	0.60	0.06	9.81	0.00	0.48	0.72
		Physical Activity	-0.66	0.06	-10.77	0.00	-0.78	-0.54
		Fruit/Veg Consumption	0.02	0.01	1.35	0.18	-0.01	0.05
		Intercept	22.65	0.08	279.03	0.00	22.49	22.81
South, (105,083)								
	Sex	Female	-0.65	0.05	-14.42	0.00	-0.74	-0.56
	Race/Ethnicity	AmericanIndian	1.04	0.20	5.09	0.00	0.64	1.44
		Asian	-1.44	0.13	-11.48	0.00	-1.68	-1.19
		Black	1.25	0.07	18.93	0.00	1.12	1.38
		Hispanic/Latino	0.31	0.06	4.85	0.00	0.19	0.44
		NHOPI	-0.30	0.28	-1.07	0.28	-0.84	0.25
		Multiple non-Latino	0.47	0.09	5.26	0.00	0.30	0.65
	Grade	Tenth Grade	0.55	0.05	9.99	0.00	0.44	0.65
		Eleventh Grade	0.95	0.05	17.54	0.00	0.84	1.06
		Twelfth Grade	1.17	0.07	15.78	0.00	1.02	1.31
	Year	Survey Year	-0.03	0.02	-1.57	0.12	-0.06	0.01
	Behavior	Depression	0.51	0.05	10.68	0.00	0.42	0.61
		Physical Activity	-0.63	0.04	-14.99	0.00	-0.71	-0.55
		Fruit/Veg Consumption	0.05	0.01	3.70	0.00	0.02	0.08
		Intercept	22.74	0.07	332.76	0.00	22.61	22.88
West, (72,686)								
	Sex	Female	-0.76	0.08	-8.97	0.00	-0.93	-0.59
	Race/Ethnicity	American Indian	2.21	0.29	7.73	0.00	1.65	2.77
		Asian	-0.36	0.42	-0.86	0.39	-1.18	0.46

Table 5 Continued

		Black	1.02	0.27	3.79	0.00	0.49	1.55
		Hispanic/Latino	1.70	0.14	12.48	0.00	1.43	1.96
		NHOPI	1.61	0.25	6.36	0.00	1.12	2.11
		Multiple non-Latino	0.56	0.26	2.19	0.03	0.06	1.07
	Grade	Tenth Grade	0.51	0.16	3.27	0.00	0.20	0.81
		Eleventh Grade	1.20	0.17	7.12	0.00	0.87	1.53
		Twelfth Grade	1.45	0.20	7.16	0.00	1.05	1.85
	Year	Survey Year	0.05	0.03	1.57	0.12	-0.01	0.12
	Behavior	Depression	0.41	0.11	3.69	0.00	0.19	0.63
		Physical Activity	-0.42	0.13	-3.31	0.00	-0.67	-0.17
		Fruit/Veg Consumption	0.00	0.04	-0.05	0.96	-0.08	0.08
		Intercept	21.90	0.14	155.03	0.00	21.62	22.17

Table 6 shows the regression analysis including regions as dummy variables. This analysis was conducted to investigate if geographic region is associated with BMI. The sample size for this analysis was 271,427.

Table 6: Region and BMI Regression Model

Construct	Variable	Coef.	SE	T-score	P-value	95% CI	
Sex	Female	-0.71	0.03	-23.61	0.00	-0.77	-0.65
Race/Ethnicity	American Indian	1.28	0.15	8.73	0.00	0.99	1.56
	Asian	-0.96	0.21	-4.54	0.00	-1.38	-0.55
	Black	1.29	0.05	26.07	0.00	1.19	1.39
	Hispanic Latino	0.98	0.06	15.62	0.00	0.86	1.11
	NHOPI	0.69	0.17	4.10	0.00	0.36	1.03
	Multi	0.51	0.08	6.13	0.00	0.35	0.68
Year	Survey Year	0.02	0.01	2.06	0.04	0.00	0.05
Grade	Ten	0.55	0.04	13.88	0.00	0.48	0.63
	Eleven	1.03	0.05	21.80	0.00	0.94	1.12
	Twelve	1.23	0.06	20.43	0.00	1.11	1.35
Region	Northeast	0.34	0.10	3.40	0.00	0.14	0.54
	Midwest	0.40	0.09	4.49	0.00	0.23	0.58
	South	0.51	0.09	5.97	0.00	0.34	0.68
Behavior	Depression	0.53	0.03	17.33	0.00	0.47	0.59
	Physical Activity	-0.60	0.04	-15.69	0.00	-0.67	-0.52
	Fruit/Veg Consumption	0.02	0.01	1.72	0.09	0.00	0.04
	Intercept	21.91	0.13	162.96	0.00	21.65	22.18

Table 7 shows data for an analysis to examine if there is an interaction between the behavioral variables and the region of which a respondent resides. In this case, the column “P-value” displays relative significance of a behavioral variable’s association with BMI compared to the Northeast. Comparatively, the column “Int-P” represents inter-region comparisons of the strengths of these within region associations. These analyses adjusted for sex, race, and grade as the other analyses but are not listed in the table. Each of the adjustment variables were significantly different by region ($p<0.01$).

Table 7: Interaction of Behavioral Variables and BMI Between Regions

Variable	Region	Coef	SE	T-score	P-value	95% CI		Int - P
Physical Activity								
n=420,118	Midwest	-0.06	0.05	-1.26	0.21	-0.16	0.04	0.01
	South	0.01	0.04	0.17	0.86	-0.08	0.10	0.01
	West	0.11	0.05	2.19	0.03	0.01	0.20	0.01
	Intercept	21.84	0.06	382.92	0.00	21.72	21.95	
Depression								
n=459,052	Midwest	-0.05	0.05	-1.06	0.29	-0.14	0.04	0.00
	South	-0.08	0.04	-1.97	0.05	-0.16	0.00	0.00
	West	-0.26	0.04	-5.95	0.00	-0.34	-0.17	0.00
	Intercept	21.46	0.05	398.93	0.00	21.35	21.56	
Fruit and Veg								
n=309,201	Midwest	0.03	0.02	1.76	0.08	0.00	0.07	0.00
	South	0.08	0.02	4.61	0.00	0.05	0.12	0.00
	West	0.05	0.02	2.54	0.01	0.01	0.09	0.00
	Intercept	21.87	0.08	286.87	0.00	21.72	22.02	

4.1 Hypothesis Results

Hypothesis 1

The first hypothesis in this study is that dietary consumption of fruit and vegetables will be inversely related to BMI in all four regions of the US during the sampling period. No significant inverse relationships of BMI and fruit and vegetable consumption were observed in these analyses. This is indicated by the complete model data from Table 6 for fruit and vegetable consumption. However, data from Table 5 indicate that one significant relationship between BMI and diet found was for the Southern US, and this relationship was a positive association between eating fruits and vegetables and BMI of respondents in this region. Based on the coefficient, the relationship indicates that for every one unit increase in fruit and vegetable consumption, there will be an average increase in BMI of 0.05 kg/m^2. As this is the only significant relationship found, we cannot reject the null hypothesis H_{01}.

Hypothesis 2

The second hypothesis in this study is that there is a significant inverse association between being physically active for at least 60 minutes per day for at least five days of the week and BMI. Each of the four regions showed a significant inverse association with this physical activity variable as displayed in Table 5. This is supported by a significant inverse association observed in the model data from Table 6 for the physical activity behavioral variable. Furthermore, data from Table 5 show that respondents who report being physically active for at least five days in the past week, compared to those who do not report this measure of physical activity, see a decrease of 0.64, 0.66, 0.63, and 0.42 kg/m^2 to their BMI on average in the Northeast, Midwest, South, and West respectively. To clarify with an example, this tells us that if a respondent from the Northeast reports being physically active for five days in the past week, their predicted BMI will be 0.64 kg/m^2 lower on average compared to a respondent who did not report this level of physical activity. This means we can reject the null hypothesis H_{02}.

<u>Hypothesis 3</u>

The third hypothesis in this study is that there will be a significant positive association between self-reported depression and BMI. Each of the four regions showed a significant positive association with this measure as displayed in Table 5. These results show that respondents who report being depressed, compared those who do not report being depressed, see an increase of 0.67, 0.60, 0.51, and 0.41 kg/m^2 to their BMI on average in the Northeast, Midwest, South, and West respectively. Therefore, we can reject the null hypothesis H_{03}.

<u>Hypothesis 4</u>

The final hypothesis in this study is that the associations of childhood obesity behavioral variables – dietary consumption of fruits and vegetables, physical activity, and depression will vary in their strength of association to BMI across regions of the US.

Table 7 shows data from analyses using STATA's indicator command as well as a parameter test to investigate the overall significance of these strength differences. Not all interaction terms were significant within each region, however all regions showed statistically different strengths of these behavioral variables (Int-P) in their contribution to BMI between each other. Therefore, we can reject the null hypothesis H_{04}.

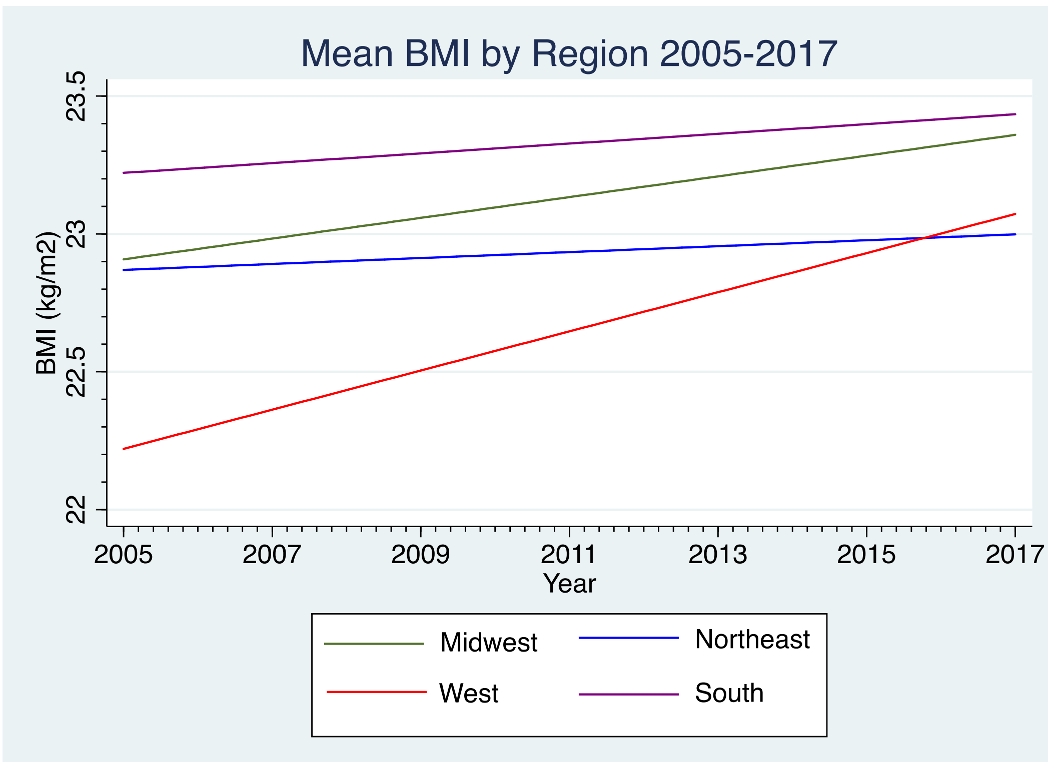

Figure 2: Mean BMI by Region 2005-2017

5.0 Discussion

Using the social-ecological model as a theoretical basis for exploring the public health problem of childhood obesity, this study sought to investigate if measures of dietary consumption of fruits and vegetables, exercise, and the mental health of 12-17 year olds were associated with BMI in each of the four regions of the US from 2007 to 2017. Additionally, this study attempted to investigate if the strength of these associations differed between regions of the US during 2007 to 2017.

Hypotheses 2, 3, and 4 were able to reject the null, however hypothesis 1 was unable to do so. Examining dietary consumption of fruit and vegetables, as was explored here, did not indicate any significant absolute or relative associations with BMI of the respondents across regions. Interestingly though, based on results of the interaction analyses we are able to conclude that the strength of observed relationships of this measure did vary significantly between regions. In other words, these associations of dietary fruit and vegetable consumption to BMI were not themselves statistically significant, but only differed significantly in the strength of which they were associated. This supports hypothesis 4, in that the observed strength of associations were different between regions. This could suggest some factors that are unique to the regions of the US contribute to a difference in how dietary fruit and vegetable consumption can contribute to BMI.

Additionally, as Table 5 shows the South region was the only region to display a significant association between this dietary measure within the respondents of the region itself. This seems to explain why in Table 7 the South region showed the most significant difference in strength of association of dietary fruit and vegetable consumption compared to the other regions. This p-value of less than 0.01 and coefficient of 0.08 indicates that the South region, for every one unit increase of fruit and vegetable consumption, will on average relate to an increase of 0.08 kg/m^2 in BMI. Interestingly, this association is a positive association and is not in line with any hypotheses proposed here.

Analyses relating to physical activity showed significant inverse associations with respondent BMI in all four regions as displayed in Table 5, allowing for the rejection of null hypothesis H_{02}. Furthermore, physical activity is associated with a decrease in BMI regardless of region as Table 6 shows. It does not come as much of a surprise that more physical activity is associated with a decreased BMI on average, but it is interesting that regions differed in their relative strengths of this association.

The West displayed the strongest relative association of physical activity and BMI. This means that compared to the other regions, the respondents in the West may exhibit a greater change in BMI on average as a result of changes to their physical activity habits. These results indicate that there may be cultural, behavioral, or local community factors in the West that are different from the other regions regarding being physically active. The diversity of terrain in the West provides opportunity for a wider range of outdoor activities than other regions of the US. With beaches, mountains, deserts, and valleys, there is a greater number of activities that can be chosen from to participate in physical activity. Perhaps this is an example of a local factor that gives people in the West greater motivation, excitement, or interest in being physically active compared to other areas of the US.

The examination of mental health (depression) using YRBS data in this study were in line with that of physical activity in terms of significant associations to BMI. The main difference in the associations seen with depression was a positive association with reported depression and BMI, whereas physical activity showed the inverse of this. In other words, as respondents reported being depressed, they were more likely to show an above average BMI compared to a lower than average BMI in the physical activity measure.

Table 5 showed that each region displayed a significant association of reported depression to BMI independent of one another, with the Northeast region showing the strongest association relative to the other three regions. This observation of reported depression and BMI in the Northeast is emphasized in Table 7, where each region shows a negative coefficient. This means that, in terms of reported depression, the Midwest, South, and West show a weaker interaction of the region's influence on associations with BMI relative to the Northeast. This indicates that respondents in the Northeast may be subject to different cultural norms surrounding mental health stigma, whether that means willingness to report depression, mental health service availability, or some other community factor – warrants further investigation.

Again, Table 7 shows the strength of interactions for each behavioral variable relative to the Northeast region. These data show valuable information about how differences in geographic region of the respondents may help to inform just how much a specific known contributor of childhood obesity relates to BMI relative to another region. These data do not represent the absolute relationships of the behavioral variables to BMI that are displayed in Table 5 but do show how associations change when examined across regions. Based on the coefficients displayed in Table 7, the Northeast region displays the strongest relative interaction with depression and BMI, the South with fruit and vegetable consumption and BMI, and the West with physical activity and BMI.

These findings all represent important pieces of the puzzle to conquering the problem of childhood obesity and may help guide policy making decisions that focus on childhood obesity prevention. As some public health programs and interventions aim to change behaviors in a way that is cost-effective and sustainable, these data can help guide planning and implementation of public policies or interventions by better informing lawmakers and private funders.

For example, as physical activity held the greatest relative strength of association with BMI in the West, an intervention that focuses on physical activity as a means to prevent childhood obesity may be a better choice than one that focuses on dietary changes. In other words, since physical activity in the West has a stronger relative association to a reduction in BMI, it may make more sense to go for the sure thing than to try and modify a behavior with less of a relationship to BMI in that specific region. Additionally, a state-wide or county-based law in the West that requires schools to include more physical activity into a yearly curriculum may hold more impact than one focusing on diet or mental health.

6.0 Limitations

These analyses were conducted under the knowledge that each of the regions were significantly different in terms of race, sex, grade, and (for Midwest only) survey year. The analyses performed here should not guide decision making about the impact of dietary fruit and vegetable consumption on BMI, as no significant associations were observed in terms of this behavioral variable's overall contribution to respondent BMI. This study did not examine relationships specifically based on sex or race, and the strengths of associations within those groups may be different than the overall results. Socioeconomic data was unavailable in the initial dataset; however, inclusion of these data may elicit more accurate representations of regional trends in behaviors. Some students from the four regions of the US are likely not included because they did not take the survey. This could be a result of general refusal, incarceration, disability, or students absent from school during data collection and failure to complete upon return.

7.0 Conclusion

This study was able to elicit that physical activity and self-reported depression were significantly associated with respondent BMI based on YRBS data from 2007 to 2017 in all four geographic regions of the US. Additionally, each of the four geographic regions of the US showed significant differences in the strength of interactions of behavioral variables – physical activity, dietary fruit and vegetable consumption, and self-reported depression – to their relationship with respondent BMI.

Further investigations into these relationships could potentially help direct future research into proper approaches to reducing risk for childhood obesity based on geographic location in the US. Similarly, the findings discussed here can help guide the development of policies aimed at reducing the public health burden that is childhood obesity.

Appendix A Map of Regions of the United States by Census Tract [92]

Figure 3 United States Census Tracts

Source: https://www.cdc.gov/cancer/uscs/technical_notes/criteria/census-regions-divs.htm

Appendix B Codebook Link [93]

https://www.cdc.gov/healthyyouth/data/yrbs/pdf/2017/2017_YRBS_Data_Users_Guide.pdf

Appendix C Calculating Mental Health, Dietary, and Physical Activity Variables and Creating Combined Physical Activity Variable

Physical Activity – Exercise
*Answers of F,G, or H were grouped together as meeting a physical activity requirement, whereas A – E were considered 'no' answers.
Q79. During the past 7 days, on how many days were you physically active for a total of at least 60 minutes per day? (Add up all the time you spent in any kind of physical activity that increased your heart rate and made you breathe hard some of the time.)

A. 0 days
B. 1 day
C. 2 days
D. 3 days
E. 4 days
F. 5 days
G. 6 days
H. 7 days

Diet – fruit and vegetable consumption
*each response option is followed by the weight value assigned to that response
*response choices B and C are the midpoint of each range divided by 7 (days)
*Scores from each question were summed and used to create a single dietary variable for analysis

Q71. During the past 7 days, how many times did you eat fruit? (Do not count fruit juice.)

A. I did not eat fruit during the past 7 days (0)
B. 1 to 3 times during the past 7 days (0.29)
C. 4 to 6 times during the past 7 days (0.71)
D. 1 time per day (1)
E. 2 times per day (2)
F. 3 times per day (3)
G. 4 or more times per day (4)

Q72. During the past 7 days, how many times did you eat green salad?

A. I did not eat green salad during the past 7 days (0)
B. 1 to 3 times during the past 7 days (2/7=0.289~0.29)
C. 4 to 6 times during the past 7 days (5/7=0.714~0.71)
D. 1 time per day (1)
E. 2 times per day (2)
F. 3 times per day (3)
G. 4 or more times per day (4)

Q73. During the past 7 days, how many times did you eat potatoes? (Do not count french fries, fried potatoes, or potato chips.)

A. I did not eat potatoes during the past 7 days (0)
B. 1 to 3 times during the past 7 days (0.29)
C. 4 to 6 times during the past 7 days (0.71)
D. 1 time per day (1)
E. 2 times per day (2)
F. 3 times per day (3)
G. 4 or more times per day (4)

Q74. During the past 7 days, how many times did you eat carrots?

A. I did not eat carrots during the past 7 days (0)
B. 1 to 3 times during the past 7 days (0.29)
C. 4 to 6 times during the past 7 days (0.71)
D. 1 time per day (1)
E. 2 times per day (2)
F. 3 times per day (3)
G. 4 or more times per day (4)

Q75. During the past 7 days, how many times did you eat other vegetables? (Do not count green salad, potatoes, or carrots.)

A. I did not eat other vegetables during the past 7 days (0)
B. 1 to 3 times during the past 7 days (0.29)
C. 4 to 6 times during the past 7 days (0.71)
D. 1 time per day (1)
E. 2 times per day (2)
F. 3 times per day (3)
G. 4 or more times per day (4)
G. 4 or more times per day

<u>Mental Health – depression</u>

Q25. During the past 12 months, did you ever feel so sad or hopeless almost every day for two weeks or more in a row that you stopped doing some usual activities?

A. Yes (1)
B. No (0)

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