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Obesity represents a public health epidemic affecting an increasing number of children as well as adults (Hales, Carroll, Fryar, & Ogden, 2017). Obesity is associated with a multitude of negative health implications, and excessive adiposity can also weaken mental health through increasing risk of depression, anxiety, and low self-esteem (Fruh, 2017). Obese children and adolescents are more likely to become severely obese adults, making prevention and early intervention extremely important for minimizing the negative effects of obesity over time (The, Suchindran, North, Popkin, & Gordon-Larsen, 2010). Thus, identification of obesity-related modifiable behaviors can help target future obesity prevention research efforts and in turn, has the potential to improve the quality of life for many children and adolescents. Emerging adulthood, a developmental period during 18 to 25y (Nelson, Story, Larson, Neumark-Sztainer, & Lytle, 2008), is becoming increasingly important as a time when not only initial changes in markers of chronic disease risk can be seen, but as a unique opportunity for behavior change interventions (Gilmore, 2019).

Currently there is little research describing how longitudinal BMI and adolescent dietary patterns relate to obesity-related biomarkers in emerging adulthood. Furthermore, despite the evidence that children's self-regulation skills may play a role in obesity development, there is inadequate longitudinal research on how self-regulatory behaviors in childhood may affect longitudinal BMI growth. Thus, the specific aims of the proposed research included to i) characterize unique trajectories of BMI from childhood through adolescence (4 to 18 year) and describe the association between BMI trajectory membership and body composition and biomarkers in emerging adulthood; ii) determine the prospective association between pre-school self-regulation and BMI trajectory membership; and iii) describe unique patterns of adolescent dietary consumption and determine the corresponding association between adolescent dietary pattern membership and later anthropometrics and biomarkers including BMI, percent body fat, fasting glucose, fasting insulin, and HOMA-IR collected in emerging adulthood.

Data from the RIGHT Track Parent and RIGHT Track Health longitudinal studies were used to address the study aims. The combination of data from the two studies provided the necessary

data to address the study aims and included baseline sociodemographic information, childhood behavioral data, longitudinal anthropometrics throughout childhood and adolescence, adolescent dietary intake, and biomarker and body composition data collected in emerging adulthood. Participants in the RIGHT Track studies could be characterized into two unique longitudinal BMI trajectories: i) stable normal weight and ii) normal weight to overweight transition. Compared to the stable normal weight group, membership in the normal weight to overweight transition group was positively associated with fasting glucose, fasting insulin, HOMA-IR, waist circumference, and percent body fat, even after controlling for sex, race, and socioeconomic status. Results were attenuated when each model additionally controlled for adult waist circumference or adult percent body fat. Importantly, higher childhood self-regulatory behavior, as measured by a gift-delay task, decreased the likelihood of a child being in the "higher-risk", that is "normal weight to overweight transition" group. Higher childhood self-regulation as measured by a food-related task was not associated with BMI trajectory membership. However, moderate food-related self-regulation was suggestive of decreased risk of membership in the BMI transition group compared to those who were considered unregulated ($p=0.09$). Even though this relation was not statistically significant, this finding supports exploration of "consuming any foods in moderation" as a useful technique when educating children on nutrition. Finally, two unique patterns of adolescent dietary intake were found in our sample: i) balanced (higher consumption of unsweetened beverages, fruits, and non-starchy vegetables) and ii) unbalanced (greater consumption of sugar-sweetened beverages, fried potatoes, and full fat/fried meats). While there were differences in types of foods consumed by those in each of these patterns, adolescents in both patterns had an overall poor diet quality. No significant associations were found between adolescent dietary patterns and any of the adult health measures (i.e., fasting glucose, fasting insulin, HOMA-IR, percent body fat or BMI), which could possibly partially be explained by our limited number of individuals who had both dietary and biomarker data.

This study provides insight into longitudinal growth patterns for children and adolescents and corresponding childhood behavioral predictors that could serve as targets for public health interventions to decrease obesity-related health risks. Additional research is needed to examine self-regulatory behaviors at different time points during childhood to determine the best age at

which implementation of behavioral interventions would be most effective in minimizing future adiposity-related health risks.

LONGITUDINAL BMI TRAJECTORIES AND ADOLESCENT DIETARY PATTERNS IN THE RIGHT TRACK RESEARCH PROJECT

by

Ashley Lauren Paynter

A DISSERTATION

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Approved by

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DEDICATION

To my grandmother Annie-Dare Thompson who taught me about patience, hard work, and perseverance.

APPROVAL PAGE

This dissertation written by Ashley Lauren Paynter has been approved by the following committee of the Faculty of The Graduate School at The University of North Carolina at Greensboro.

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CHAPTER I: INTRODUCTION

Obesity is a serious public health issue that has been increasing in prevalence over the past few decades across most age groups (Hales et al., 2017). Research shows that during 2015 to 2016, almost 40% of adults (≥20 y) and 20.6% of adolescents (12-19 y) in the United States suffered from obesity (Hales et al., 2017). Additionally, prevalence of obesity in children has been shown to increase with age with estimates of 13.9%, 18.4%, and 20.6% for children aged 2 to 5, 6 to 11, and 12 to 19 years, respectively (Hales et al., 2017). Obesity has many negative physical health implications, especially for children and adolescents, including increased LDL cholesterol and triglyceride levels, risk factors for chronic disease, as well as increased risk of type 2 diabetes (Fruh, 2017). In addition to the physical health implications, obesity is associated with increased risk of mental health issues such as depression, anxiety, and low self-esteem (Fruh, 2017). Obesity is difficult to treat, and research shows that obese children and adolescents are more likely to become obese and severely obese adults (Lanigan, Tee, & Brandreth, 2019; The et al., 2010). Further, the earlier individuals develop obesity-related risk factors, the more likely they are to experience morbidity and mortality from obesity-related disease (Kelsey, Zaepfel, Bjornstad, & Nadeau, 2014). As such, obesity prevention has been identified as the best approach for reducing the prevalence of obesity throughout the lifetime (Lanigan et al., 2019). Thus, it is important to identify modifiable risk factors during childhood (developmental period spanning from age 6 to 10 y) (Huang, Lanza, Wright-Volel, & Anglin, 2013) and adolescence (developmental period spanning from 12/13 y to 18/19 y) (Huang et al., 2013; Wickrama, Noh, & Elder, 2009) and emerging adulthood (period spanning from approximately 18/19 y to 25 y) (Augustus-Horvath & Tylka, 2011; Wickrama et al., 2009) that could serve to minimize the likelihood of individuals transitioning to obesity in the future.

Body Mass Index (BMI) Trajectories

BMI is regularly used in obesity research and is generally accepted as a proxy measure for body fatness in both adults and children (Bouchard, 2007; Dietz & Bellizzi, 1999). As such, categorization of BMI values in adults (CDC), and BMI-for-age percentile in children under the

age of 20 (CDC), provides a measure of obesity status. BMI classifications for adults are: underweight (<18.5 kg/m^2); normal weight (18.5-<25 kg/m^2); overweight (25-<30 kg/m^2); and obese (≥30 kg/m^2), respectively (CDC). In youth, individuals with BMI values below 5% of their age-sex specific BMI-for-age percentile cut point are considered underweight, 5% to less than 85% are normal weight, 85% to less than 95% are overweight, and 95% or higher are classified as obese (CDC).

In longitudinal studies, BMI trajectories have been used to describe unique patterns of BMI change in a particular population (Clarke, O'Malley, Schulenberg, & Johnston, 2010; Moreno-Black, Boles, Johnson-Shelton, & Evers, 2016; Ostbye, Malhotra, & Landerman, 2011; Viner, Costa, & Johnson, 2019), with these patterns having associations with health outcomes in adults including diabetes, hypertension, and cancer (Clarke et al., 2010; Ostbye et al., 2011). However, adult populations are assumed to have reached constant height, so weight is the only parameter changing over time (Clarke et al., 2010; Jun et al., 2012; Ostbye et al., 2011). Additional considerations must be assessed in a population of children making their transition into adolescence given that their height is changing in addition to their weight, with this resulting in a corresponding increase in BMI as a normal part of growth. Thus, BMI in non-adult populations is interpreted on an age-sex specific basis, utilizing data and analysis tools provided by the Centers for Disease Control (CDC). (CDC; CDC) Previous research has shown that childhood BMI trajectories are associated with adult health-related outcomes such as waist circumference (Peneau et al., 2017) and hyperglycemia (T. Zhang et al., 2019).

The literature describing growth trajectories in children and adolescents varies in choice of outcome measure with researchers choosing between BMI (Kubzansky, Gilthorpe, & Goodman, 2012; Nonnemaker, Morgan-Lopez, Pais, & Finkelstein, 2009), BMI percentile (Huang et al., 2013; Kwon, Janz, Letuchy, Burns, & Levy, 2017), and BMI standard deviation score/BMI z-score (Geserick et al., 2018; Prinz et al., 2018). Cole et al. suggest that BMI or BMI percentile are more appropriate measures to assess longitudinal adiposity in children, with BMI z-score being recommended as a measure of fatness at a single time point (Cole, Faith, Pietrobelli, & Heo, 2005). However, findings from the Fels Longitudinal Study, which assessed a wider age range of children than Cole et al., concluded that changes in BMI percentile does not necessarily represent corresponding adiposity changes in children, with the relation between BMI percentile

and adiposity being affected by both BMI and sex (Demerath et al., 2006). Additionally, when assessing longitudinal change, due to the skewed nature of BMI, changes in BMI percentile translate to larger BMI changes for those at or above the 95th percentile as compared to those at the 50th percentile (Cole et al., 2005). Thus, choice of BMI outcome measure can influence the interpretation of study results, especially in the context of BMI change (Cole et al., 2005; Demerath et al., 2006). Therefore, the present study will utilize trajectories of BMI.

Choice of Modelling Framework

Researchers have utilized both growth mixture modelling (GMM) (Clarke et al., 2010; Jun et al., 2012; Kubzansky et al., 2012) and latent class growth analysis (LCGA) (Huang et al., 2013; Ostbye et al., 2011; Slining, Herring, Popkin, Mayer-Davis, & Adair, 2013) frameworks to develop trajectories of BMI. The main difference between these frameworks is that LCGA, a specialized subset of GMM, requires subjects within the same trajectory to be homogeneous, whereas GMM allows for within trajectory heterogeneity (Jung & Wickrama, 2008; B. Muthén, 2006). Given that each framework comes with its own benefits, our research will fit models using both GMM and LCGA and utilize corresponding fit statistics to identify the best-fitting model (B. Muthén, 2006).

Decision Criteria for Choosing Best Fitting Model

Bayesian Information Criteria (BIC) is the primary criteria used to determine adequate model fit in GMM and LCGA modelling, with smaller values representing better fitting models (Masyn, 2013). However, sometimes differences between BIC values for multiple models can be quite small, indicating a "minimal gain" in model fit with the addition of more classes (Masyn, 2013). According to Raftery et al., a difference in BIC greater than 10 provides "very strong evidence" to support that the model with the smaller BIC is the better fitting model with odds of 150:1 (Raftery, 1995). In addition to BIC, entropy can further inform the choice of the best fitting model. Values of entropy approaching 1.0 indicate better class delineation, with a value of 1.0 indicating perfect model delineation, and a value greater than 0.8 supporting that classes have been clearly defined (Celeux & Soromenho, 1996; Tein, Coxe, & Cham, 2013). Although entropy can be used in combination with BIC during the model selection process, since entropy was not developed to identify the appropriate number of latent classes in the GMM/LCGA

frameworks, BIC will be the primary criteria to assess model fit (Masyn, 2013). Finally, the Lo-Mendell-Rubin likelihood ratio test (LMR LRT) compares the fit of two models, a model with k classes versus a model with k-1 classes, with a significant p-value indicating that the k-class model more accurately fits the data (B. Muthen, 2004).

Time Centering

Centering of the time variable in growth modelling, which is age in the proposed analysis, will affect interpretation of model estimates and should be based on the research question being addressed (Biesanz, Deeb-Sossa, Papadakis, Bollen, & Curran, 2004; Hamaker & Grasman, 2014; Raudenbush & Bryk, 2002). While model fit will not be affected by time centering, model estimates and their corresponding interpretation will depend on the method of time coding (L. K. Muthén & Muthén, 2010). Primary coding options include no centering, centering at the grand mean, centering at the cluster mean, or centering at a theoretical point of interest such as study initiation, study midpoint, or puberty (Hamaker & Grasman, 2014). The primary goal of centering is to allow for interpretability of the model intercept because without centering, the intercept of the model, an age of zero in this instance, has no meaningful interpretation (Biesanz et al., 2004).

A potential time point for centering in the current study would be the theoretical onset of puberty, as this marks a series of important physical changes that have been shown to be associated with future health outcomes (Abreu & Kaiser, 2016). However, age at puberty onset has very large individual variation and is dependent on race and sex, with puberty onset averaging between 8 to 12 years for females and 9 to 14 years for males (Abreu & Kaiser, 2016). Furthermore, both early and delayed puberty are not uncommon (Abreu & Kaiser, 2016). Additionally, the derived BMI trajectories will be utilized by all RIGHT Track researchers and as such there is no single theoretical time point that would be applicable to all future study-related research questions. Thus, a study-specific centering point would be more appropriate than puberty onset.

One study-specific centering point would be age at baseline measure, which would allow interpretation of our linear term as initial baseline growth rate (Raudenbush & Bryk, 2002). However, a potential issue that arises with baseline centering is the increase in collinearity of the

linear and quadratic terms in our growth model and is a concern for this study given the increased number of available data points (Raudenbush & Bryk, 2002). A solution for this collinearity is to center time to the midpoint age of the study. For our quadratic growth model, midpoint centering not only results in the meaningful interpretation of our linear coefficient as the average growth rate during the study, but also reduces the correlation between our linear and quadratic age terms (Raudenbush & Bryk, 2002). For this study, the midpoint age of data collection for anthropometric measurements is approximately 11 years. This further allows for general application of derived BMI trajectories for research questions posed by all RIGHT Track investigators.

Covariate Adjustment

Inclusion of covariates in latent class derivation is an important consideration. When a covariate is added to the model, odds ratios can be obtained that indicate if membership in a particular latent class as compared to the referent class is more or less likely at varying levels of the covariate (Lanza & Rhoades, 2013). Additionally, Hu et al. reported that for analyses with small sample sizes of approximately 400 individuals, inclusion of covariates in GMM provided better model performance (J. Hu, Leite, & Gao, 2017). Covariates of interest that have association with BMI trajectories included sex (Paynter, Koehler, Howard, Herring, & Gordon-Larsen, 2015), race (Isong, Richmond, Avendano, & Kawachi, 2018), and socioeconomic status (SES) (Jansen, Mensah, Nicholson, & Wake, 2013). Given these considerations and our limited sample size of less than 400 participants, multinomial logistic regression will be utilized to determine if the aforementioned covariates are predictors of the BMI trajectory classes obtained from unconditional GMM analyses (Magee, Caputi, & Iverson, 2013). Significant predictors will be added to the best-fitting unconditional model to obtain the final conditional trajectory results (Jung & Wickrama, 2008; Magee et al., 2013).

Biomarkers, Waist Circumference, and Body Composition

Biomarkers are biological measurements that can be used in research and clinical settings to not only diagnose particular disease states, but can additionally provide insight into future disease risk (Choong & Tsafnat, 2012). Insulin resistance has been identified as an important cardiovascular risk factor (Adeva-Andany, Martinez-Rodriguez, Gonzalez-Lucan, Fernandez-Fernandez, & Castro-Quintela, 2019) and fasting glucose, fasting insulin, and Homeostatic

Model Assessment of Insulin Resistance (HOMA-IR) are the primary biomarkers used to identify individuals with insulin resistance (Singh & Saxena, 2010). Fasting glucose levels at or above 126 mg/dl on at least two separate occasions, or a glucose value of at least 200 mg/dl at any single measurement, are the current standard for diagnosis of diabetes (Gedela, Appa Rao, & Medicherla, 2007), however, measuring insulin levels has the important ability to identify insulin resistance prior to the appearance of clinical signs of metabolic disease (Singh & Saxena, 2010). Thus, collecting data on insulin values in addition to glucose can be used to compute corresponding HOMA-IR levels to provide estimates on beta-cell function and insulin resistance (Singh & Saxena, 2010).

In addition to biomarkers, measures of body shape and body composition have been shown to be associated with metabolic functioning (Lee, Bacha, Gungor, & Arslanian, 2006). Waist circumference, as a proxy for abdominal fatness, has been shown to relate to insulin sensitivity in children, with larger waist circumferences being associated with decreased insulin sensitivity (Lee et al., 2006). Further, body composition, as assessed by percentage of body fat, has association with HOMA-IR in adolescent populations (Wedin, Diaz-Gimenez, & Convit, 2012).

BMI Trajectories, Biomarkers, and Body Composition

Research utilizing latent class analysis for derivation of childhood BMI trajectories have consistently detected three to four distinct BMI growth patterns, with most studies identifying a stable overweight or obese group and a rapid BMI increase group amongst these patterns (Mattsson et al., 2019). A recent systematic review of latent-class derived BMI trajectories identified nine studies conducted in non-infant populations like that of RIGHT Track. Of these nine studies, three measured adult outcomes with these including anthropometrics (height, weight, waist circumference), body composition (fat mass, subscapular skinfolds), biomarkers (fasting glucose, lipids, blood pressure), and mortality (all-cause and cancer-specific) (Mattsson et al., 2019). However, only a single study utilized BMI to derive trajectories and also assessed associations between trajectory membership and adult non-mortality health markers (Mattsson et al., 2019; Peneau et al., 2017). Péneau et al. found that trajectories characterized by a stable 75th BMI-for-age percentile or BMI increases were associated with increased adult BMI and waist circumference, however no significant association was found between trajectory membership and adult fasting glucose (Mattsson et al., 2019; Peneau et al., 2017). An additional study

described the association between childhood BMI z-score trajectories and adult BMI and fat mass finding that trajectories marked by early rapid increase in BMI z-score, whether persistent or non-persistent, were associated with higher BMI and fat mass in adulthood (Mattsson et al., 2019; Rzehak et al., 2017).

A review of studies not included in the systematic review by Mattsson et al. showed that while long-term growth trajectories utilizing BMI standard deviation scores from 4y to 18y were not associated with adult biomarkers including HDL, diastolic BP, or inflammatory markers (Oluwagbemigun et al., 2019), research conducted via derivation of childhood BMI trajectories showed that membership in early onset adiposity trajectories was associated with higher adolescent BP (Munthali, Kagura, Lombard, & Norris, 2016). A GMM analysis conducted in a sample of females aged 5y to 15y showed significantly higher insulin resistance and fasting insulin levels in a BMI trajectory group marked by rapid increase of BMI percentiles, but found no significant differences in fasting glucose amongst the four distinct BMI trajectory groups (Ventura, Loken, & Birch, 2009). However, this study did not include adult biomarker data and excluded males (Ventura et al., 2009). Further, childhood BMI trajectories developed in a Finnish sample were associated with type 2 diabetes status in adulthood (Eriksson, Kajantie, Lampl, & Osmond, 2015). To add to the existing literature, the derived BMI trajectories in this study will be utilized to determine associations with future obesity-related risk factors including fasting glucose, levels of insulin resistance, and percent body fat collected in emerging adulthood.

Self-regulation and BMI

Self-regulation is an expression used to describe a wide variety of behaviors including emotional regulation, delay of gratification, and effortful control (Anzman-Frasca, Francis, & Birch, 2015). Emotional regulation encompasses a set of strategies that children often employ when dealing with various stressful or difficult situations requiring them to control certain impulses (Power et al., 2016), while delay of gratification describes a child's ability to forego an immediate reward in order to obtain a more desirable future reward (Schlam, Wilson, Shoda, Mischel, & Ayduk, 2013). The term effortful control is a child's ability to voluntarily alter their attention and behaviors in situations even when this alteration is not desired by the child (Eisenberg, 2012). Effortful control encompasses attention regulation and behavioral regulation, with behavioral

regulation including activational control and inhibitory control (Eisenberg, 2012). Inhibitory control, a measure of self-regulatory ability, is defined as one's capacity to abstain from a particular behavior in response to instruction or command (Goldsmith). According to a systematic review, low levels of self-regulation have been shown to have association with higher BMI in infants and pre-school aged children (Bergmeier, Skouteris, Horwood, Hooley, & Richardson, 2014). Additionally, inability to self-regulate, as measured by lab-assessed tasks, was associated with larger increases in BMI (Bergmeier et al., 2014). Most interestingly, poor emotional regulation measured at 2y was a stronger predictor of future risk of overweight at 5.5 y (Bergmeier et al., 2014).

Similar findings have been discovered for measures specifically assessing the inhibitory control aspect of self-regulation. Research conducted in a sample of German children and adolescents aged 8 to 15 showed that low levels of inhibitory control, as measured by a go/no go laboratory task, were associated with higher BMI measures (Pauli-Pott, Albayrak, Hebebrand, & Pott, 2010). Another study conducted in German primary school children demonstrated obese children were more likely to exhibit lack of inhibitory control as compared to normal weight subjects (Wirt et al., 2014). Similarly, a study of US adolescent lean and obese females used fMRI to assess brain regions associated with inhibitory control during a go/no-go task (Batterink, Yokum, & Stice, 2010). Researchers found that subjects with higher BMI values exhibited lower inhibitory control in response to visual stimuli depicting desserts (Batterink et al., 2010).

While Balantekin et. al. explored the relation of childhood inhibitory control and adolescent BMI related to female adolescent weight control behavior patterns (Balantekin, Birch, & Savage, 2015), to our knowledge, there are no current studies that look at the relation between childhood inhibitory control, as measured by food and non-food tasks, and BMI trajectory membership. Thus, the proposed research will describe the association between pre-school inhibitory control and membership in a particular BMI trajectory, with these results potentially serving to inform future studies seeking to intervene at this critical point in development to positively influence BMI change over time and reduce future health risks.

Diet

Dietary intake is a modifiable behavior that is associated with obesity (Iannotti & Wang, 2013b). Many analyses of diet in children and adolescents rely on assessment of specific food groups or pre-specified dietary indices, such as the Healthy Eating Index (HEI) or Dietary Approaches to Stop Hypertension (DASH) scores, which use the sum of scores for intake of individual food components to determine an overall score (Berz, Singer, Guo, Daniels, & Moore, 2011; Costacou et al., 2018). While high diet quality as measured by these indices is associated with decreased risk of cardiovascular disease and type 2 diabetes (Schwingshackl, Bogensberger, & Hoffmann, 2018), overall diet quality of young adults does not meet current nutrition recommendations (Lipsky et al., 2017). Similarly, in populations with similar diet quality, these diet-quality indices can produce homogeneous scores which may not be useful for identification of groups with unique dietary patterns. For example, individuals with similar diet-quality scores may consume different types of food, even though their HEI scores are classified as low quality (NCI).

However, dietary patterns allow researchers to better understand how overall dietary intake may vary in populations with similar diet quality. Additionally, dietary patterns can describe how overall diet is associated with health outcomes rather than being limited to studying single food or nutrient relation (Rocha, Milagres, Longo, Ribeiro, & Novaes, 2017). In this regard, studying dietary patterns not only provides a more comprehensive view of dietary intake, but also contributes information on potential synergistic effects of foods (Rocha et al., 2017).

Diet Assessment Measures

Two primary diet data collection tools are utilized in studies assessing dietary patterns including 24-hour dietary recalls and food frequency questionnaires (FFQ) (Cunha et al., 2018). The FFQ provides a list of food items to an individual who then estimates the typical amount of servings they consume of each item within a particular time frame (i.e., month, year) (Looman, Boshuizen, Feskens, & Geelen, 2019). These assessments provide a measure of an individual's usual dietary intake and are typically used in large research studies since they do not require additional study staff to administer and can be completed relatively quickly (Looman et al., 2019). Dietary assessment via 24-h recalls on the other hand requires increased time and resources as trained study staff are needed to obtain more detailed information related to dietary intake via a multiple-pass method (Looman et al., 2019). While 24-h recalls are expensive to

administer, they provide more detailed nutrient information for the date of assessment (Looman et al., 2019). However, to obtain an estimate of a person's habitual intake using 24-h recalls, multiple interviews on various days are necessary (Looman et al., 2019). The current study will use dietary data from 24-h recalls obtained from a multiple-pass telephone procedure; FFQ data are not available in this sample (Wideman et al., 2016).

Comparison of Methodology for Derivation of Dietary Patterns

Primary methods used to derive dietary patterns include confirmatory (Togo, Heitmann, Sorensen, & Osler, 2003) and exploratory (LeCroy et al., 2019) factor analysis (CFA and EFA), principal component analysis (PCA) (Bertin et al., 2016; Maia et al., 2018; J. Zhang et al., 2015), and latent class analysis (LCA) (Iannotti & Wang, 2013a; Sotres-Alvarez, Herring, & Siega-Riz, 2010). The main difference between these various methods of dietary pattern derivation is that CFA, EFA, and PCA serve to identify foods commonly eaten in combination (i.e., correlated food items), whereas LCA classifies individuals into mutually exclusive groups with similar food consumption (Sotres-Alvarez et al., 2010). An advantage of LCA over other methods is that risk of a particular outcome can be estimated and compared for each identified group (Sotres-Alvarez et al., 2010). Thus, LCA will be utilized in the proposed analysis to derive groups of individuals with unique dietary intake to compare how BMI trajectory membership differs by dietary pattern.

Dietary Patterns and Biomarkers

Previous studies have established links between certain dietary patterns and metabolic risk factors, including Homeostatic Model Assessment of Insulin Resistance (HOMA-IR) levels, and fasting glucose, however most of these studies were cross-sectional in nature (Rocha et al., 2017). A systematic review by O'Neil et al. found that studies consistently identified a relation between 'less healthy' dietary patterns (i.e., patterns marked by increased sweet and savory snack consumption) and poor mental health status in children and adolescents (O'Neil et al., 2014). Further, a meta-analysis conducted by Cunha et al. indicated that consumption of 'unhealthy' dietary patterns was associated with increased BMI and WC (Cunha et al., 2018). While the studies summarized by Cunha et al. identified dietary patterns in various way, these 'unhealthy' dietary patterns tended to follow a Western diet including foods such as pizza, processed and high fat meats, and sugar-sweetened beverages and desserts (Cunha et al., 2018).

Research in a sample of Mexican adolescents identified three dietary patterns corresponding to westernized, prudent, and high protein/high fat diets (Gutierrez-Pliego, Camarillo-Romero Edel, Montenegro-Morales, & Garduno-Garcia Jde, 2016). Data showed that the westernized and high protein/fat patterns were correlated with higher BMI values (Gutierrez-Pliego et al., 2016). Additionally, a study of Chinese children and adolescents found that dietary patterns characterized by increased intake of fast food and simple carbohydrates were associated with increased risk of obesity (J. Zhang et al., 2015). However, these studies were cross-sectional that identified dietary patterns via PCA rather than LCA.

Although Wright et al. described the relation between adult BMI and longitudinal patterns of protein intake from childhood to adulthood (Wright, Sotres-Alvarez, Mendez, & Adair, 2017), dietary patterns of children and adolescents, particularly as they relate to adult biomarkers, have not been well described in US populations. The proposed research hopes to fill this gap by describing the relation between adolescent dietary patterns and health markers in emerging adulthood.

Study Design and Analysis Population

Overview

Data from the Research Investigating Growth and Health Trajectories (RIGHT) Track and RIGHT Track Health longitudinal studies. The RIGHT Track and RIGHT Track Health longitudinal studies examine developmental changes in social, emotional, and physical health from childhood to early adulthood (Wideman et al., 2016). The baseline study population included three cohorts of children from central North Carolina, with approximately 37% of the sample being considered at risk for future behavioral issues (Wideman et al., 2016).

Participants were recruited via program services such as day care centers, County Health Departments, and Women, Infants, and Children (WIC) services and were representative of the surrounding community in terms of race and SES (Wideman et al., 2016). Potential participants for cohorts 1 and 2 were recruited at 2-years of age (cohort 1: 1994-1996 and cohort 2: 2000-2001) and screened using the Child Behavior Checklist (CBCL) (Achenbach, 1992), completed by the mother, in order to over-sample for externalizing behavior problems. Children were

identified as being at risk for future externalizing behaviors if they received an externalizing T-score of 60 or above. Efforts were made to obtain approximately equal numbers of males and females. This recruitment effort resulted in a total of 307 children. Cohort 3 was initially recruited when infants were 6 months of age (in 1998) for their level of frustration, based on laboratory observation and parent report, and were followed through the toddler period (S.D. Calkins, Dedmon, Gill, Lomax, & Johnson, 2002). Children from Cohort 3 whose mothers completed the CBCL at two-years of age ($N = 140$) were then included in the larger study.

Of the entire RIGHT Track sample ($N = 447$), 37% of children were identified as being at risk for future externalizing problems. There were no significant demographic differences between cohorts regarding gender, $\chi^2(2, N = 447) = 0.63$, $p = 0.73$, race, $\chi^2(2, N = 447) = 1.13$, $p = 0.57$, or two-year SES, $F(2, 444) = 0.53$, $p = 0.59$. Additional details of the RIGHT Track study design and sample description are provided in Wideman et al.(Wideman et al., 2016) These longitudinal data not only provide insight into a unique sample of children but also capture crucial periods of their development.

STUDY VARIABLES

Data describing psychological factors were obtained from participants beginning at age 2, with subsequent data collection points at 4, 5, 7 and 10 years of age (Wideman et al., 2016). Collection of corresponding health and biomarker data was initiated at approximately 16 years of age. Participant anthropometric measures of height and weight were measured by trained staff at 11 visits corresponding to an age range of 3 to 25y. Dietary assessment was conducted in a subset of participants using three 24-hour dietary recalls, two week-day and one weekend day, via one-on-one phone-based interviews at approximate ages 16(T1), 19(YA1), and 23(YA2) (Wideman et al., 2016). Preliminary analyses characterized longitudinal patterns of BMI and adolescent dietary patterns in the RIGHT Track study population via two derived categorical variables. These derived variables will be used to determine the association between longitudinal BMI patterns and a variety of psychological, behavioral, and physiological factors, including self-regulation of behavior, patterns of dietary intake, fasting glucose levels, and percent body fat. Detailed descriptions of analysis variables are provided below and summarized in Table 1.

Demographic Information

Sex, race, and Hollingshead index of **SES** (Hollingshead, 1975) at age 2 will be used as possible covariates and/or to describe membership characteristics of subjects in each BMI trajectory and dietary pattern. Of note, given minimal sample size in non-white race categories, race will be analyzed as a dichotomous variable with levels 'Caucasian' and 'non-Caucasian' (African American, biracial, and other). In the RIGHT Track sample, SES at age 2 ranges from 40 to 54 reflecting minor professional and technical occupations considered to be representative of middle class (Hollingshead, 1975).

Behavioral Data

This research utilizes data from two different laboratory tests performed at age 4 as measures of inhibitory control. Tests were modelled after those described in the Laboratory Temperament Assessment Battery (Lab-TAB) (Gagne, Van Hulle, Aksan, Essex, & Goldsmith, 2011; Goldsmith, Reilly, Lemery, Longley, & Prescott, 1995). The first task, **snack delay**, involved a researcher presenting a child with an M&M candy but making the child wait two minutes before allowing them to eat the candy (Blandon, Calkins, Keane, & O'Brien, 2010). During this task, the researcher remained in the room standing beside the child for the full experiment time. The proportion of time not touching the item will be used as another measure of inhibitory control, with higher numbers indicating better control. The second task was a **gift delay** experiment during which participants were given a wrapped gift and instructed to not open it for two minutes (Graziano, Calkins, & Keane, 2010). Once presented with the gift box, researchers left the room and observed the child's behavior to determine the total time the child touched the gift. This analysis will use the proportion of time not touching the gift to denote levels of inhibitory control, with higher numbers resulting in better control (Graziano et al., 2010).

Anthropometrics and Biomarkers

Lab measured height was measured to the nearest 0.1cm (collected via measuring tape (RIGHT Track) and stadiometer (RIGHT Track Health)) and **weight** was measured to the nearest 0.1 kg (collected via analog scale (RIGHT Track) and balance beam scale (RIGHT Track Health)) (Graziano, Kelleher, Calkins, Keane, & Brien, 2013; Wideman et al., 2016). Height and weight

data will be used to compute **BMI** (kg/m^2) values at all visits ranging from age 4 to less than 20 years of age. **Percent body fat**, measured via bod pod, fasting serum glucose, and **HOMA-IR** were obtained at three time points corresponding to emerging adulthood. The most recent time point for which non-missing adult ($\geq$ 18 years) biomarker data are available will be included in these analyses (Wideman et al., 2016).

Dietary Data

Data from the 24-hour dietary recalls collected via NDSR software at the T1, YA1, and YA2 time points will be used to derive **dietary patterns**. Diet recalls were collected for a subset of participants. Participants were contacted at two of three time points corresponding to approximate ages 16, 20, and 23 years. For each time point, the protocol was to obtain three diet recalls: two weekday recalls and one weekend day recall. A total of 266 individuals had at least 3 diet recalls summing across all available time points.

Table 1. Description of Analysis Variables

	Type	Interpretation	Time points‡
Demographics:			
Sex	Categorical	1=Male 2=Female	2
Race	Categorical	1=Caucasian 2=African American, Biracial, and Other	2
SES	Continuous	Hollingshead Index of Socioeconomic Status	2
*Child's age**	Continuous	Age in years	4, 5, 7, 10, Pilot, Temp15, Temp17, T1, T2, YA1, YA2
Anthropometrics/Biomarkers			
Height (cm)	Continuous	Height in centimeters	4, 5, 7, 10, Pilot, Temp15, Temp17, T1, T2, YA1, YA2
Weight (kg)	Continuous	Weight in kilograms	4, 5, 7, 10, Pilot, Temp15, Temp17, T1, T2, YA1, YA2
BMI (kg/m^2)	Continuous	Body Mass Index	4, 5, 7, 10, Pilot, Temp15, Temp17, T1, T2, YA1, YA2
Body fat (%)	Continuous	Percent Fat Mass	T2, YA1, YA2

	Type	Interpretation	Time points‡
*Fasting glucose (*mg/dL*)*	Continuous	Serum Fasting Glucose	T2, YA1, YA2
HOMA-IR	Continuous	Homeostatic Model Assessment of Insulin Resistance	T2, YA1, YA2
Self-regulation			
Inhibitory control (non-food)	Continuous	Effortful Control Gift Delay (Proportion of NOT touching gift)	4
Inhibitory control (food)	Continuous	Effortful Control Snack Delay (Proportion of NOT touching food)	4
Derived Variables**			
BMI trajectories	Categorical	1=Stable normal weight 2=Normal weight to overweight transition	4, 5, 7, 10, Pilot, Temp15, Temp17, T1, T2
Adolescent dietary patterns	Categorical	1=Balanced 2=Unbalanced	T1, YA1

‡ Time points described based on RIGHT Track study naming conventions. Time points 2, 4, 5, 7, 10 correspond to desired age of data collection; Pilot corresponds to pilot study for RIGHT Track Health (average age of 16); Temp15 and Temp17 correspond to laboratory visits to assess temperament measures at desired ages of 15 and 17; T1 and T2 correspond to pre-adult biomarker visits (average age of 16 and 17, respectively); YA1 and YA2 correspond to laboratory visits for collection of young adult biomarker data (average age of 19 and 23, respectively).

* Restructured age variable computed from denoted time points

** Data from corresponding time points were utilized in variable derivation

*** Baseline time point for anthropometric measures varies for each individual (ranges from 3.5 to 5.5 years)

CHAPTER II: ASSOCIATION BETWEEN BODY MASS INDEX TRAJECTORIES FROM CHILDHOOD TO ADOLESCENCE WITH ADIPOSITY AND BIOMARKERS IN EARLY ADULTHOOD

This chapter is an article draft prepared for submission to Obesity (Silver Spring).

Abstract

Objective: Childhood obesity has been cross-sectionally linked to health issues such as hypertension, dyslipidemia, and type 2 diabetes, however, the relation between longitudinal BMI growth patterns in children and future health markers remains less explored. The focus of this study was to derive unique patterns of longitudinal BMI growth in children aged 4 to 17 years and determine the relation between trajectory membership and early adulthood metabolic and anthropometric measures.

Methods: Growth mixture models (GMM) were used to derive trajectories of BMI growth from age 4 to 17 years in 357 children participating in the Research Investigating Growth and Health Trajectories (RIGHT) Track and RIGHT Track Health longitudinal studies. Linear regression models were used to assess the relation of childhood BMI trajectory and selected health markers collected in early adulthood (18 to 21 years), including metabolic biomarkers (fasting glucose, insulin, and HOMA-IR) and anthropometrics (percent body fat and waist circumference).

Results: We identified two distinct BMI trajectories corresponding to “stable normal weight” and “normal weight to overweight transition” groups. Compared to the stable normal weight group, membership in the normal weight to overweight transition group was positively associated with all outcome measures after controlling for sex, race, and socioeconomic status. Results were attenuated when additionally controlling for adulthood waist circumference (WC) or percent body fat; however, in models adjusting for adulthood percent body fat in addition to baseline characteristics, the association between BMI trajectory membership and insulin, HOMA-IR, and WC remained significant.

Conclusions: We identified trajectories of BMI from childhood into adolescence and showed these trajectories were associated with metabolic and anthropometric measures in adulthood. This study shows the relation between longitudinal childhood BMI patterns and adult cardiometabolic health markers, with this relation being apparent in individuals as young as eighteen years of age. It is important to identify at-risk groups who could most benefit from intervention strategies implemented in early life.

Introduction

Obesity, or having body fat in excess of what is optimal, is a serious public health issue that is associated with increased risk of chronic diseases such as type 2 diabetes, cardiovascular disease, and even some cancers (Dietz & Bellizzi, 1999; Fruh, 2017). In addition to the physical health implications, obesity is associated with increased risk of mental health issues such as depression, anxiety, and low self-esteem (Fruh, 2017). Obesity prevalence has been increasing over the past few decades, with this trend also observed in children and adolescent populations (Hales et al., 2017). Individuals with obesity during childhood and adolescence are five times as likely to be obese in adulthood as compared to non-obese children (Simmonds, Llewellyn, Owen, & Woolacott, 2016). Further, the earlier individuals develop obesity-related risk factors, the more likely they are to experience morbidity and mortality from obesity-related disease (Kelsey et al., 2014). As such, it is important to determine how age of obesity onset and corresponding duration and longitudinal changes in obesity status influence health.

BMI is regularly used in research as a generally accepted proxy measure for body fatness, or obesity, in both adults and children (Bouchard, 2007; Dietz & Bellizzi, 1999). Categorization of BMI values in adults (CDC), and age-sex specific BMI percentile in children under the age of 20 (CDC), is often employed as a measure of obesity status. However, adult populations are assumed to have reached constant height, so weight is the only parameter changing over time (Clarke et al., 2010; Jun et al., 2012; Ostbye et al., 2011). Additional considerations exist in a population of children making their transition into adolescence given that their height is changing in addition to their weight, with this resulting in a corresponding increase in BMI as a normal part of growth and maturation.

Latent class growth models (LCGM) and growth mixture models (GMM) are often used to group together individuals with similar longitudinal trajectories, or patterns of growth (Ram & Grimm, 2009). Longitudinal studies in adults have utilized group-based BMI trajectories to describe unique patterns of BMI change in a particular population, with these BMI patterns being associated with future health problems including diabetes, hypertension, and cancer (Clarke et al., 2010; Ostbye et al., 2011). BMI trajectories have been explored in children, with many research studies focusing on maternal and childhood predictors of future BMI trajectory membership (Lane, Bluestone, & Burke, 2013; Li, Goran, Kaur, Nollen, & Ahluwalia, 2007; Magee et al., 2013; Nedelec, Miettunen, Mannikko, Jarvelin, & Sebert, 2020; Pryor et al., 2011). Maternal factors such as higher maternal pre-pregnancy BMI and maternal smoking (Li et al., 2007; Magee et al., 2013; Pryor et al., 2011), child-level indicators such as increased birth weight (Nedelec et al., 2020), and lower socioeconomic status (Lane et al., 2013) have been shown to increase the risk of transitioning to overweight or obese status during childhood.

The literature describing growth trajectories in children and adolescents varies in choice of outcome measure with researchers using BMI (Kubzansky et al., 2012; Nonnemaker et al., 2009), BMI percentile (Huang et al., 2013; Kwon et al., 2017), and BMI standard deviation score/BMI z-score to derive trajectories (Geserick et al., 2018; Prinz et al., 2018). Cole et al. suggest that BMI or BMI percentile are more appropriate measures to assess longitudinal obesity in children, with BMI z-score being recommended as a measure of fatness at a single time point (Cole et al., 2005). However, findings from the Fels Longitudinal Study, which assessed a wider age range of children than Cole et al., concluded that changes in BMI percentile do not necessarily represent corresponding adiposity changes in children, with the relationship between BMI percentile and adiposity being affected by both BMI and sex (Demerath et al., 2006). Additionally, when assessing longitudinal change, due to the skewed nature of BMI, changes in BMI percentile translate to larger BMI changes for those at or above the 95th percentile as compared to those at the 50th percentile (Cole et al., 2005). Thus, choice of BMI outcome measure can influence the interpretation of study results, especially in the context of BMI change, and for longitudinal research seeking to understand obesity changes in children and adolescents, BMI is recommended (Cole et al., 2005; Demerath et al., 2006).

While relations between childhood obesity, as defined by increased BMI values, and future health issues such as hypertension, dyslipidemia, type 2 diabetes, and some cancers have been shown cross-sectionally (Weihrauch-Bluher, Schwarz, & Klusmann, 2019) the relation between longitudinal BMI growth patterns in children and future health markers remains less explored (Oluwagbemigun et al., 2019). Previous research has shown childhood BMI trajectories are associated with adult health-related outcomes such as blood pressure and hypertension (Yuan et al., 2020), waist circumference (Peneau et al., 2017), hyperglycemia (T. Zhang et al., 2019), and type 2 diabetes (Yuan et al., 2020). While Oluwagbemigun *et al*. showed the association between BMI trajectory membership and hypertension and inflammatory markers in late adolescence (Oluwagbemigun et al., 2019), there is limited information related to the relation between childhood BMI trajectories and metabolic markers and insulin resistance in later life. Emerging adulthood (18-25y) is a time in the lifespan that is increasingly of interest to researchers since the appearance of chronic disease risk factors can occur during this time (Hoare, Dash, Jennings, & Kingwell, 2018). In addition, emerging adulthood serves as a unique period where individuals become more independent (Arnett, 2000), representing an important time to encourage behavior changes to promote health and decrease future health risk.

The aim of the present study was to derive unique longitudinal patterns of BMI in children during 4 to 17 years of age and determine the association of these patterns with selected measures of cardiometabolic health collected in emerging adulthood (18-25y). To our knowledge, this is the first study to determine the association between childhood BMI trajectories and adult insulin status and insulin resistance.

Methods

Study Design and Participants

This study included 357 children from the Research Investigating Growth and Health Trajectories (RIGHT) Track (1996 - 2015) (S. D. Calkins & Keane, 2009) and RIGHT Track Health longitudinal studies (2014-2021) (Wideman et al., 2016). Together, these two studies examined developmental changes in social, emotional, and physical health from childhood to early adulthood in a total of 447 children (Wideman et al., 2016). Three cohorts of participants were recruited via program services in central North Carolina such as day care centers, County

Health Departments, and Women, Infants, and Children (WIC) services, with participants being representative of the surrounding community in terms of race and socioeconomic status (SES) (Wideman et al., 2016).

Participants for cohorts 1 and 2 were recruited at 2-years of age (cohort 1: 1994-1996 and cohort 2: 2000-2001; n=307) and screened using the Child Behavior Checklist (CBCL) (Achenbach, 1992), completed by the mother, in order to over-sample children considered at risk for future behavioral issues. Participants in cohort 3 were recruited at 6 months of age (in 1998) for their level of frustration, based on laboratory observation and parent report, and were followed through the toddler period (S.D. Calkins et al., 2002). Children from cohort 3 whose mothers completed the CBCL at two-years of age (n=140) were then included in the RIGHT Track studies. A total of ten laboratory visits took place during the combined studies corresponding to ages 2, 4, 5, 7, 10, 15, 16, 17, 18, and 23. Demographic and anthropometric data were collected at each time point, however, anthropometrics were not collected at age 2. Demographic information was obtained via parent survey. More detailed information related to study design and recruitment has been published previously (S.D. Calkins et al., 2002; Graziano et al., 2010; Wideman et al., 2016).

Participants were eligible for inclusion in the current study if they had at least two BMI measures during 4 to 17 years of age (n=357). As our primary objective was to develop BMI trajectories from childhood through adolescence, only longitudinal anthropometrics prior to age 18 were utilized. Due to missingness of baseline covariates, the final analytic sample totaled 342 individuals.

DEMOGRAPHICS

Sex, race, and socioeconomic status (SES) were utilized as covariates in all analyses. SES was computed via Hollingshead four factors score, which utilizes an individual's education level (ranging from 1=less than 7th grade to 7=graduate degree) and occupation (ranging from 1= unskilled laborers to 9=executives/major professionals) to compute a composite score (Hollingshead, 1975). An aggregate measure of SES is then computed by multiplying education level by a factor of 3 and occupation by a factor of 5 and then summing these two values; total SES scores range from 8 to 66. If both parents in a family unit were employed, their individual

scores were averaged to form the final SES score. Scores were interpreted as follows: unskilled laborers (8-19), semi-skilled workers (20-29), sales workers/skilled craftsmen (30-39), minor professional (40-54), and major business (55-66) (Hollingshead, 1975). Race was reported as 'Caucasian,' 'African American,' 'Biracial,' and 'Other,' however, minimal sample sizes in non-White race categories led to the dichotomization of race as 'Caucasian' and 'non-Caucasian'.

Longitudinal Anthropometrics

Height and weight were measured by trained staff at laboratory visits at ages 4, 5, 7, 10, 15, 16, 17, 18 and 25 years (Graziano et al., 2013; Wideman et al., 2016). During the visits prior to 15 years of age, height was measured to the nearest 0.1 cm with a measuring tape and weight was measured to the nearest 0.10 kg with an analog weight scale (Graziano et al., 2013). More precise measurement instruments were available during the RIGHT Track Health study, and so height was collected via stadiometer to the nearest 0.1 cm (SECA, Chino CA) and a balance-beam scale was used to measure weight to the nearest 0.1 kg (Detecto-medic, Brooklyn NY) (Wideman et al., 2016). BMI (kg/m^2) and age-sex specific BMI percentile were computed at each time point using the SAS macro produced by the Centers for Disease Control and Prevention (CDC).

Adult Anthropometrics and Biomarkers

Additional anthropometric measures and biomarker data were collected during the RIGHT Track Health study. Waist circumference was taken at the smallest part of the abdominal area and measured using a Gulick tension-tape measure to the nearest 0.1 cm. Percent body fat was measured via a daily calibrated BOD POD following standard measurement protocol (Cosmed, Concord, CA, USA). Fasting serum glucose (mg/dl) and fasting insulin (pg/mL) were obtained via colorimetric assay (Caymen Chemical, Ann Arbor, MI) for participants at approximately 18 and 23 years of age. Insulin was converted from pg/mL to g/mL by a factor of 10^{-3} and g/mL to µIU/mL via a factor of 28.8 (Knopp, Holder-Pearson, & Chase, 2019). Insulin values will be reported in both µIU/mL and pmol/L for ease of comparison to other studies. As such, µIU/mL was converted to pmol/L via a factor of 6.00 as recommended in Knopp et al (Knopp et al., 2019). HOMA-IR, a measure of insulin resistance, was computed via fasting insulin (µIU/mL) x fasting glucose (mg/dl)]/405 (Rivas-Crespo, 2015). The earliest time point for which the

participant's non-missing adult biomarker data were available (i.e., > 18 years) was used in analyses. Additional details related to anthropometric and biomarker data collection procedures and protocols are described further in Wideman et al (Wideman et al., 2016).

Statistical Methods

Growth mixture modeling (GMM) (B. Muthen) was conducted to derive groups with unique longitudinal BMI trajectories using Mplus analysis software (version 8; 2017). GMM is used to identify unobservable, or latent, groups within a population of interest using observed longitudinal data (Ram & Grimm, 2009). GMM methods provide information on how these latent groups change over time and allow for comparison of these latent groups to explore differences in these longitudinal changes (Ram & Grimm, 2009). GMM analyses require a data structure with minimal variability of participant age at each time point (B. O. Muthen & Khoo, 1998). In the current study, participant age differed by up to two years at various laboratory visits, requiring data restructuring to ensure equal spacing of time for BMI measures. The restructured data consisted of 10 time points corresponding to ages 4, 5, 6, 7, 8, 10, 11, 15, 16, and 17 and ensured that all time points in derived trajectories preceded adult outcome measures.

A quadratic GMM was fit to these data to account for the BMI growth pattern expected in children spanning the ages in the current study (B. Muthen & Asparouhov, 2015). While the general recommendation is for quadratic growth models to only include individuals with at least three repeated outcome measures, if the majority of subjects have three or more observations, the analysis sample can include participants with only one or two observations (Curran, Obeidat, & Losardo, 2010). Thus, our inclusion criteria ensured that an individual's data at minimum contributed information towards the prediction of the model's intercept and linear slope. Subsequent model selection for GMM analyses was performed in four major steps.

Step one was to determine the appropriate constraints for variance and covariance parameters in a two-class model. In a standard latent class growth model (LCGA) all variance and covariance parameters are set to zero, which in turn forces individuals within the same latent class to be homogenous. GMM, however, allows all variance and covariance parameters to differ, thus allowing for heterogeneity within a particular latent class (Jung & Wickrama, 2008). In the current study, four sets of constraints were tested: 1) a fully constrained LCGA (i.e., variance of

intercept, linear, and quadratic terms forced to zero), 2) a GMM which allowed all variance and covariance parameters to vary freely (i.e., variance of intercept, linear, and quadratic terms allowed to vary and covary), 3) a GMM with quadratic growth constrained to zero for all classes (i.e., variance of intercept and linear term allowed to vary and covary with the quadratic term forced to zero for all classes), and 4) a GMM with quadratic growth constrained to zero for only a single class (i.e., variance of intercept, linear, and quadratic term allowed to vary and covary for one class and variance of intercept and linear term allowed to vary and covary with the quadratic term forced to zero for the second class only).

Step two applied constraints from the best-fitting two-class model identified in step one to models with increasing number of latent classes. In step three, multinomial logistic regression was used to model class membership, as identified by the best-fitting model from step two, as a function of pre-identified covariates to identify significant predictors of class membership. Addition of significant covariates in a GMM allow for more accurate estimation of the intercept, linear slope, and quadratic parameters for each latent class (Jung & Wickrama, 2008). As such, in the fourth and final step, significant predictors of latent class membership were added to the best-fitting model in step two as covariates to produce the final estimates (Magee et al., 2013).

Model fit was evaluated after steps one, two, and four and was assessed by multiple criteria including (1) the Bayesian Information Criteria (BIC), with smaller values representing better fitting models (Masyn, 2013), (2) entropy, with values greater than 0.8 supporting that classes have been clearly defined and a value of 1.0 indicating perfect model delineation (Celeux & Soromenho, 1996; Tein et al., 2013), and (3) the Lo-Mendel-Rubin likelihood ratio test (LMR LRT), which compares the fit of a model with k classes versus a model with k-1 classes (B. Muthen, 2004). Individuals were then classified into a trajectory based on their highest posterior class membership probability. There are no formal rules to define a minimum required percentage for class membership, but recommendations suggest a minimum of 5% (Andruff, Carraro, Thompson, & Gaudreau, 2009).

BMI Trajectories and Adult Health Markers

Multiple linear regression models were used to separately assess the relation between BMI trajectory membership and percent body fat, waist circumference, fasting glucose, fasting

insulin, and HOMA-IR in emerging adulthood. All non-normally distributed adult health markers (fasting glucose, fasting insulin, and HOMA-IR) were log-transformed via natural logarithm. A series of four linear regression models were used to examine the relation between the BMI trajectory membership and each outcome variable: 1) unadjusted model with BMI trajectory membership alone, 2) demographic adjusted model controlling for race, sex, socioeconomic status, 3) demographic adjusted model additionally controlling for waist circumference in adulthood, and 4) demographic adjusted model additionally controlling for body fat percentage in adulthood. Due to issues related to the collinearity of waist circumference and percent body fat ($r = 0.60$), these variables were not included in the same model and as such two separate models, (3) and (4), were fit.

Chi-square and Student's t-tests were used to determine if baseline characteristics differed by BMI trajectory membership and significance was assessed at alpha = 0.05. Regression analyses and tests of baseline characteristics were conducted in SAS version 9.4.

Results

Our analytic sample of 342 participants was comprised of 153 males and 189 females, was primarily Caucasian, and middle class (Table 2). Overall, on average, participants maintained BMI values corresponding to normal weight throughout the study with age-sex specific BMI percentiles between the 50th and 75th percentiles at all data points (CDC).

BMI TRAJECTORY DERIVATION

All GMMs had better fit as compared to LCGA models with the GMM allowing for heterogeneity of variance for all terms for class one while constraining the variance for the quadratic term for class two had the best fit overall (see Appendix A1). The 3-class model produced the lowest BIC, had a significant LMR LRT p-value, and the decrease in BIC from the 2-class to the 3-class model was approximately 17, providing 'very strong' evidence in support of the 3-class model (see Appendix A2) (Raftery, 1995).

Table 2. Baseline Demographics and Adult Health Markers of RIGHT Track Sample Overall and by BMI Trajectory Membership

	Overall	Stable Normal Weight	Overweight Transition	p-value[1]
n (%)	349	272 (77.9)	77 (22.1)	

Sex, n (%)				0.103
Male	153 (45.8)	131 (48.2)	29 (37.7)	
Female	189 (54.2)	141 (51.8)	48 (62.3)	
Race, n (%)				<0.001
Caucasian	229 (65.6)	194 (71.3)	35 (45.5)	
African-American & Other	120 (34.4)	78 (28.7)	41 (54.6)	
SES, mean (std)	39.7 (10.9)	40.8 (10.5)	35.9 (11.6)	<0.001
Adulthood outcomes [mean, (std)]				
BMI (kg/m^2)	26.3 (6.63)	23.8 (3.73)	33.4 (7.93)	<0.001
Body fat percentage	26.7 (12.43)	23.0 (10.34)	37.5 (11.22)	<0.001
Fasting glucose (mg/dL)	77.8 (16.16)	76.6 (11.48)	82.6 (26.30)	<0.001
Fasting insulin (µIU/mL)	38.9 (32.29)	33.9 (26.01)	55.8 (43.92)	<0.001
Fasting insulin (pmol/L)	233.8 (193.8)	203.5 (156.07)	335.1 (263.5)	<0.001
HOMA-IR	7.7 (7.56)	6.5 (5.22)	12.1 (12.10)	<0.001
Waist circumference (cm)	82.8 (16.59)	77.2 (10.85)	98.2 (19.96)	<0.001

[1]p-values from chi-square tests for frequencies and t-tests for means

However, with inclusion of covariates race and SES, which were identified as significant predictors of class membership in a multinomial logistic regression model (see Appendix A3), the LMR LRT p-value for the 3-class model became non-significant, indicating that the 2-class model with covariates was a better fit. A logistic model for the 2-class model confirmed the same significant predictors of class membership as for the 3-class model (see Appendix A4). A significant LMR LRT, in combination with the limited sample size in class 3 (n = 23, 7%) and the larger entropy value in the 2-class model, led to the decision to utilize the trajectories identified by the 2-class model with covariates for regression analyses.

The primary difference between the 2-class and 3-class models was the identification of a 'stable obese' class (n = 23). Of note, all participants classified as 'stable obese' in the 3-class model were classified as 'normal to overweight transition' in the 2-class model. Due to the clinical relevance of a stable obese BMI trajectory as 'high risk' (Buscot et al., 2018), visual representation of the 3-class model is provided in the Appendix as reference (Appendix A5); regression results for the 2-class model, excluding the 23 individuals assigned to the 'stable obese' class as identified by the 3-class model are provided as a sensitivity analysis.

COMPARING BMI TRAJECTORY CLASS CHARACTERISTICS

The two mean BMI trajectories are presented in Figure 1. Class 1 (n = 272, 77.9%) was stable normal weight as defined by average BMI percentiles below 85% throughout the growth period (Table 2, Figure 2) (CDC). Contrastingly, on average, Class 2 (n = 77, 22.1%) transitioned from normal weight to overweight during the study, with BMI percentiles increasing from below 85% to above 85%, with this change occurring between ages 5 and 7 (Figure 2). Thus, we use the following descriptors for classes 1 and 2 respectively: 1) stable normal weight and 2) normal weight to overweight transition.

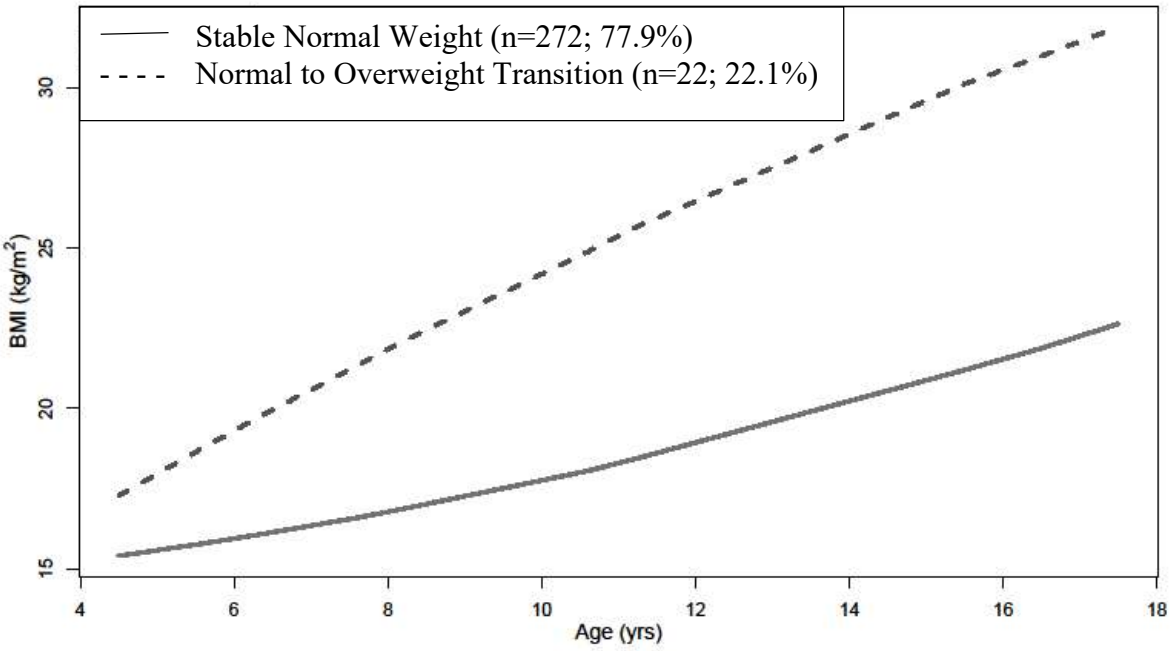

Figure 1. Longitudinal BMI Trajectories for Stable Normal Weight and Normal to Overweight Transition Groups

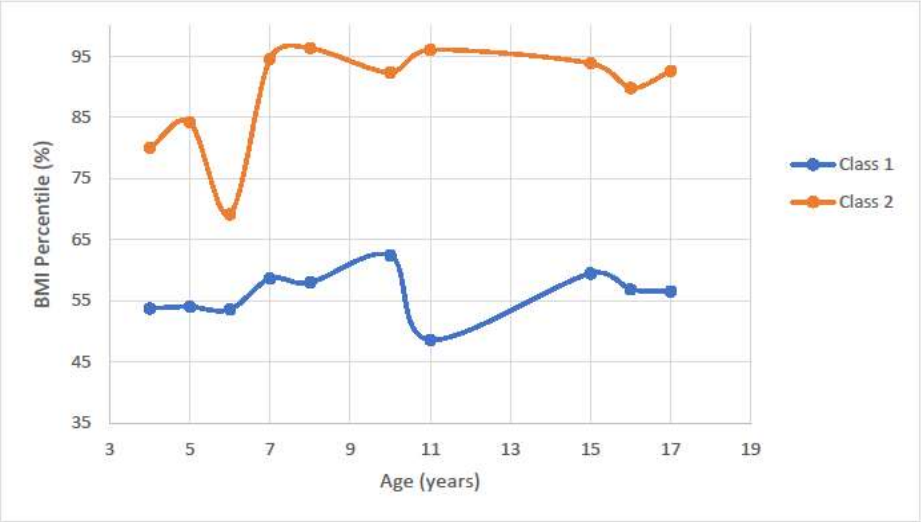

Figure 2. Average BMI percentile by BMI Trajectory Class Membership over Time

The stable normal weight group consisted of a higher proportion of Caucasian participants as compared to the overweight transition group. Even though both classes could be described as lower middle-class with average SES values nearing 40, members of the overweight transition group had lower SES as compared to those in the stable normal weight group (Hollingshead, 1975). As expected, there were no significant sex differences when comparing classes; computation of BMI for children and adolescents is age and sex specific and sex was not a significant predictor of class membership as described in the GMM analysis process.

When comparing unadjusted mean values of adult metabolic markers and anthropometrics, the overweight transition group had significantly higher values as compared to the stable normal weight group (Table 2). On average, fasting glucose, fasting insulin, and HOMA-IR were 6 mg/dL, 22uIU/mL, and 5.6 units higher in the overweight transition group as compared to the stable normal weight group, respectively. Similarly, average BMI (d=9.6 kg/m^2), body fat percentage (d=14.5 %), and waist circumference (d=21 cm) were higher in the overweight transition group as compared to the stable normal weight group.

Association between BMI Trajectory and Biomarkers

A significant association was found between BMI trajectory class and young adulthood biomarkers for all outcomes in unadjusted regression models, with this relation holding true after adjustment for race, sex, and SES (Table 3). Demographic-adjusted models showed membership

in the overweight transition group was associated with increased percent body fat (11.3%) and waist circumference (16.2cm) and 6.5%, 40.8% and 47.0% percent increase in fasting glucose, fasting insulin, and HOMA-IR, respectively as compared to the stable normal weight group.

When further adjusting models for adulthood percent body fat, the association of BMI trajectory with fasting insulin and HOMA-IR levels remained significant, with membership in the overweight transition group being associated with a 40.5% and 44.0% higher fasting insulin and HOMA-IR respectively as compared to the stable normal weight group. The association between BMI trajectory and adult fasting glucose was no longer significant after adjustment for adulthood percent body fat.

Table 3. Linear Regression Coefficients[1] (95% Confidence Intervals) for Association between Adult Metabolic Markers and Anthropometrics and Membership in a Normal to Overweight Trajectory

	Model 1		Model 2[2]		Model 3[3]		Model 4[4]	
Outcome	b (95%CI) [n]	p-value	b (95%CI) [n]	p-value	b (95%CI) [n]	p-value	b (95%CI) [n]	p-value
% BF	11.99 (8.23, 15.74) [200]	<0.001	11.32 (8.06, 14.57) [198]	<0.001	1.92 (-0.572, 4.42) [196]	0.130	N/A	N/A
Fasting Glucose (mg/dL)	6.04 (0.477, 11.61) [218]	0.034	6.46 (0.650, 12.28) [214]	0.030	1.89 (-4.28, 8.07) [214]	0.546	2.02 (-4.85, 8.90) [187]	0.562
Fasting Insulin (μIU/mL)	40.1 (12.17, 67.94) [201]	0.005	40.8 (11.96, 69.69) [198]	0.006	22.3 (-8.98, 53.61) [198]	0.161	40.5 (5.94, 75.08) [172]	0.022
HOMA-IR	46.2 (17.19, 75.12) [199]	0.002	47.0 (17.01, 77.01) [196]	0.002	23.8 (-8.43, 56.02) [196]	0.147	44.0 (8.30, 79.68) [171]	0.016
WC (cm)	16.84 (12.30, 21.39) [230]	<0.001	16.24 (11.63, 20.84) [226]	<0.001	N/A	N/A	6.58 (2.83, 10.34) [196]	<0.001

[1] Stable Normal Weight group is the referent class. Regression coefficient for %BF and WC outcomes is the mean difference between the two classes. The reported regression coefficients for fasting glucose, fasting insulin, and HOMA-IR were multiplied by 100 and are interpreted as the percentage of change in the outcome for being in the Normal to Overweight Transition group compared to the referent Stable Normal Weight group since fasting glucose, fasting insulin, and HOMA-IR were natural log transformed.

[2] Adjusted for race, sex, socioeconomic status.

[3] Adjusted for race, sex, socioeconomic status, and waist circumference at young adulthood (WC).

[4] Adjusted for race, sex, socioeconomic status, and body fat percentage at young adulthood (% BF).

Models that adjusted for waist circumference in addition to demographic characteristics resulted in attenuated and non-significant findings for all outcomes, indicating adult waist circumference is more significantly associated with adult biomarkers than childhood BMI trajectory. Sensitivity analyses that excluded the 23 individuals identified as 'stable obese' by the 3-class model produced similar results (see Appendix A6).

Discussion

The main purpose of the current study was to characterize longitudinal trajectories of BMI growth throughout childhood and adolescence and determine the relation between these trajectories and adult anthropometrics and metabolic health markers in the RIGHT Track Research Project. We found two unique BMI trajectories from childhood to adolescence: one corresponding to stable normal weight and the other being characterized by a transition from normal weight to overweight, with this transition occurring between ages 5 and 7 (Figure 2).

Trajectory membership was significantly associated with fasting insulin, HOMA-IR, and waist circumference in adulthood, with these values being significantly higher among the overweight transition group compared to the stable normal weight group, even after adjusting for demographics and adulthood percent body fat. However, in models adjusted for adult waist circumference, these associations were attenuated. While we did see that unadjusted average fasting glucose values were higher for the overweight transition group as compared to the stable normal weight group (Table 2), both groups were, on average, below the 100 mg/dL cut point used to identify a prediabetic threshold, and as such both groups would be classified as having normal fasting glucose levels (Johnson, Duick, Chui, & Aldasouqi, 2010).

An unexpected finding was that over half of our sample (59.6%) had fasting insulin levels above 25 μIU/mL (or 150 pmol/L using a conversion factor of 6) (Knopp, Holder-Pearson, & Chase, 2019), indicating high risk of metabolic dysfunction and prediabetes (Johnson et al., 2010). Of note, only 7% of those with elevated insulin levels additionally had elevated fasting glucose levels (i.e., $\geq$ 100 mg/dL) (Lopez-Jaramillo, Velandia-Carrillo, Gomez-Arbelaez, & Aldana-Campos, 2014). This is concerning as most readily available testing methods focus on measuring fasting glucose, and based on this information alone, over 90% of those at high risk for prediabetes in our sample would have failed to be identified. Further, we were unable to identify

fasting insulin reference ranges for non-adult populations. As such, derivation of age-specific references ranges for fasting insulin as an important area for future research. This would allow for earlier identification of high-risk individuals and provide additional time for necessary intervention strategies to be applied.

BMI Trajectory Derivation and Class Characteristics

Other studies utilizing latent class growth analysis or growth mixture modeling for derivation of childhood BMI trajectories have consistently detected three to four distinct BMI growth patterns (Garden, Marks, Simpson, & Webb, 2012; Liu et al., 2017; Mattsson et al., 2019; Peneau et al., 2017). While our initial results did identify three trajectories, sample size limitations in combination with non-significant difference in model fit of the 2-class versus 3-class GMM with covariates, resulted in our final determination of two unique BMI trajectories. Further, most studies of childhood BMI trajectories have identified a stable overweight or obese group and a rapid BMI increase group amongst the trajectory groups, with this increase typically resulting in a crossing of BMI percentiles (Garden et al., 2012; Liu et al., 2017; Mattsson et al., 2019; Peneau et al., 2017). Our results are in line with past studies in that our normal weight to overweight transition group, on average, crossed multiple BMI percentiles as participants aged. Additionally, the transition from normal weight to overweight in our sample occurred between ages 5 and 7, which highlights the importance of beginning obesity prevention and intervention efforts as early as elementary school. Family-based (Berge & Everts, 2011) and school-based (Kropski, Keckley, & Jensen, 2008) obesity interventions have seen some success in reducing BMI in children, however, a majority of these interventions were not initiated until after age 7 and studies indicate that intervention strategies may need to be tailored differently based on sex (Berge & Everts, 2011; Kropski et al., 2008).

Associations of BMI Trajectory Membership and Metabolic Markers

To our knowledge, this is one of the first studies to report associations of childhood BMI trajectories and adult insulin levels. A recent systematic review of group-based BMI trajectories in children and adolescents identified only a single study conducted in a non-infant population that assessed associations between trajectory membership and adult metabolic markers, and this study did not collect fasting insulin (Mattsson et al., 2019; Peneau et al., 2017). Our results are

similar to those that have been reported in middle-aged and elderly adults such that 12-year BMI trajectories characterized by an overweight to obese transition or stable obesity had increased fasting insulin and HOMA-IR, even though these groups had similar fasting glucose values as compared to a stable normal weight BMI trajectory (Walsh, Shaw, & Cherbuin, 2018). Similarly, a GMM analysis conducted in a sample of females aged 5 to 15 years showed significantly higher insulin resistance and fasting insulin levels in adolescence for a BMI trajectory group marked by rapid increase of BMI percentiles, but found no significant differences in fasting glucose amongst four distinct BMI trajectory groups (Ventura et al., 2009). It is important to note that multiple units of fasting insulin are reported in the literature, and even though multiple conversion factors are currently accepted as accurate, different conversion factors can underestimate insulin values by up to 15% (Knopp et al., 2019).

Strengths and Limitations

A limitation of this study is that outcome measures were only available for a subset of participants, with this decreasing the sample size available for conducting regression analyses. Additionally, due to the timing of these two longitudinal studies, height and weight measurements were collected using two different sets of tools based on the gold standard tool available at the time of data collection. It is possible that measurements collected using different tools may have different levels of accuracy.

Nevertheless, the current study has several strengths that should be noted. Our study applied both GMM and LCGA frameworks to identify the best-fitting model for identifying latent BMI trajectories (B. Muthén, 2006). The main difference between these two frameworks is that LCGA, a special case of GMM, assumes subjects within the same trajectory to be homogeneous, whereas GMM allows for within trajectory heterogeneity (Jung & Wickrama, 2008; B. Muthén, 2006). We used both GMM and LCGA and utilized corresponding fit statistics to identify the model which best measured latent BMI growth patterns in our data. Additionally, the current study utilized longitudinal data spanning over 20 years, with these data providing ten age points at which BMI data were collected. Further, in addition to anthropometrics that are typically used to approximate body fatness (i.e., BMI and waist circumference), our study included objectively measured percent body fat via BOD POD. Our study contributes to the limited literature describing BMI trajectories in child and adolescent populations and corresponding associations

to adult health measures, in particular fasting insulin. Finally, this study reported insulin in multiple units, as well as conversion information, for ease of comparison for future researchers; the insulin conversion factor based on recommendations outlined in Knopp *et al*. was used (Knopp et al., 2019).

Conclusion

Earlier development of obesity-related risk factors increases the likelihood of obesity-related morbidity and mortality. Our study showed that a transition from normal weight to overweight can occur in early childhood prior to age 7. Further, this pattern of BMI increase throughout childhood and adolescence has significant health implications in emerging adulthood, such as higher insulin levels and greater likelihood of insulin resistance. Current research reports fasting insulin values in various units, and there are at least two widely used and accepted insulin conversion factors. However, choice of insulin conversion factor can underestimate true values and can have significant public health implications. The conversion factor for insulin should be standardized for the benefit of medical and public health research, and a transparent reporting of conversion factors should be encouraged. Findings of the current study demonstrate the importance of measuring multiple markers when determining metabolic health status, in addition to reporting the conversion factors used when transforming variable units. If metabolic health of this population were evaluated utilizing only fasting glucose levels, over 90% of participants in this study would be considered to have normal function, however, over half of our sample had elevated fasting insulin levels. Since insulin dysregulation occurs prior to observable glucose elevation, future research could greatly benefit from working to make methods to measure fasting insulin more accessible to the general population to identify this dysregulation before it leads to severe health issues, such as type 2 diabetes.

CHAPTER III: EARLY CHILDHOOD BEHAVIORAL REGULATION IS ASSOCIATED WITH BMI TRAJECTORIES THROUGHOUT CHILDHOOD AND ADOLESCENCE: FINDINGS FROM THE RIGHT TRACK AND RIGHT TRACK HEALTH STUDIES

This chapter is an article draft prepared for submission to the International Journal of Obesity.

Abstract

Objective: To determine the association between self-regulatory behavior at age 4 and body mass index (BMI) trajectories from childhood through adolescence.

Subjects/methods: Data from the RIGHT Track Research Project (1996-2021) were used to identify BMI trajectories from age 4 to 17 years using growth mixture models in a sample of n=334 children. Associations between BMI trajectories and childhood self-regulatory behavior at age 4, as assessed by food (snack) and non-food (gift) delay of gratification tasks, were evaluated using logistic regression.

Results: Two BMI trajectories from childhood through adolescence were identified: stable normal weight (n=272, 77.9%) and normal weight to overweight transition (n=77, 22.1%). Higher socioeconomic status was associated with membership in the stable normal weight trajectory ($p<0.01$) and non-Caucasian race was more likely than Caucasians to be in the normal weight to overweight transition trajectory ($p<0.05$). Higher levels of non-food self-regulation was predictive of membership in the stable normal weight trajectory ($p<0.01$). Food-related self-regulation was not significantly associated with trajectory membership. However, "moderate" levels of food-related self-regulation was suggestive of decreased risk of membership in the BMI transition group compared to those who were considered "unregulated" on the food task ($p=0.09$).

Conclusions: Childhood self-regulation skills warrant additional exploration as intervention targets to decrease future obesity risk. In our sample, higher levels of non-food related childhood self-regulatory behavior were associated with membership in a lower risk BMI trajectory. Even

though the relation between food-related self-regulation and longitudinal BMI growth was not statistically significant, educating children about moderation as it applies to dietary intake warrants further exploration.

Introduction

Obesity represents a public health epidemic and has many associated negative physical health implications including elevated LDL cholesterol and triglyceride levels and increased risk of type 2 diabetes (Fruh, 2017). Obese children and adolescents are more likely to become severely obese adults, with earlier development of obesity-related risk factors increasing the likelihood of obesity-related morbidity and mortality (Kelsey et al., 2014; The et al., 2010). Thus, obesity prevention has been identified as the best approach for reducing the prevalence of obesity throughout the life course (Lanigan et al., 2019). While many complex factors influence development of obesity, self-regulatory behavior has been shown to have association with body mass index (BMI) and modification of children's specific self-regulation skills may have the potential to improve current and future health outcomes (Bergmeier et al., 2014).

Self-regulation encompasses a wide variety of overlapping constructs including emotional regulation, delay of gratification, effortful control, and inhibitory control (Anzman-Frasca et al., 2015). Emotional regulation involves strategies that children use when dealing with stressful or difficult situations that require them to control certain impulses (Power et al., 2016). Delay of gratification describes a child's ability to relinquish an immediate reward in order to obtain a more desirable future reward (Schlam et al., 2013), and effortful control is a child's ability to voluntarily alter their attention and behaviors in situations even when this alteration is not desired by the child (Eisenberg, 2012). Effortful control encompasses both attention regulation and behavioral regulation, with behavioral regulation including activational control and inhibitory control (Eisenberg, 2012). Activational control describes the ability to perform a behavior whereas inhibitory control, is the capacity to abstain from a particular behavior in response to instruction or command, especially when the requested behavior is not desired by the child (Eisenberg, 2012).

Self-regulation skills begin to emerge in late infancy and different dimensions continue to develop throughout childhood and into adulthood, with some not peaking until adult years

(Anzman-Frasca et al., 2015). Children use self-regulatory behaviors to cope with stressful stimuli and given the relations between stress and various biological hunger and fullness cues, research exploring the relations between self-regulation, obesity status and eating behaviors have increased tremendously in recent years (Graziano et al., 2013). Additionally, due to the modifiable nature of self-regulatory behaviors (Anzman-Frasca et al., 2015), it is an important construct to understand as a potential target for obesity prevention.

According to a systematic review by Bergmeier et al. (2014), low levels of childhood self-regulation have been shown to have association with higher BMI in infants and pre-school aged children (Bergmeier et al., 2014). Research conducted in a sample of German children and adolescents aged 8 to 15 showed that lower levels of inhibitory control were associated with higher BMI (Pauli-Pott et al., 2010). Another study conducted in German primary school children demonstrated that obese children were more likely to exhibit lack of inhibitory control as compared to normal weight children (Wirt et al., 2014). Similarly, a study of US adolescent lean and obese females found that individuals with higher BMI values exhibited lower inhibitory control in response to visual stimuli depicting desserts (Batterink et al., 2010).

Previous research with children and adolescent females has shown that childhood inhibitory control is associated with BMI and/or weight control behavior patterns (Balantekin et al., 2015; Graziano et al., 2010; Graziano et al., 2013). To our knowledge, however, there are no current studies that assess the relation between childhood inhibitory control, as measured by both food and non-food tasks, and future patterns of BMI growth. The objective of this study was to identify the relation between modifiable childhood self-regulatory behaviors, specifically inhibitory control measured via both food- and non-food tasks, and longitudinal BMI patterns from childhood through adolescence.

Subjects and Methods

The sample of this study included children participating in the Research Investigating Growth and Health Trajectories (RIGHT) Track and RIGHT Track Health longitudinal studies, which were designed to examine developmental changes in social, emotional, and physical health from childhood to early adulthood (Wideman et al., 2016). The baseline study population consisted of three cohorts of children recruited via day care centers, health departments, and WIC services

from central North Carolina, using a mother-completed Child Behavior Checklist (CBCL) to over-sample for externalizing behavior problems (Achenbach, 1992; Wideman et al., 2016). Of the entire RIGHT Track sample (n = 447), 37% of children were identified as being at risk for future externalizing problems. There were no significant demographic differences between cohorts with regard to gender, race, or two-year socioeconomic status. RIGHT Track participants were followed from childhood through adulthood at 12 waves, with this study utilizing data from the first 10 waves corresponding to childhood and adolescence (i.e., ages prior to 18 years). Additional details related to the RIGHT Track study design and sample description are provided elsewhere (Wideman et al., 2016).

Baseline sociodemographic data were obtained at age 2 and information corresponding to behavioral factors was collected at 2, 4, 5, 7 and 10 years of age (Wideman et al., 2016). Participant anthropometric measures of height and weight were measured by trained staff at 11 visits starting at age 4.

Child Demographic Characteristics

The original 4-category race variable which included Caucasian, African American, biracial, and other, was dichotomized as Caucasian and non-Caucasian. Due to small sample sizes, subjects identifying as 'biracial' (n=16) or 'other' (n=9) were included in the non-Caucasian category.

Household Socioeconomic Status (SES)

SES was computed via Hollingshead four factors score, which utilizes an individual's education level and occupation to compute a composite score. Education level is multiplied by a factor of 3, occupation is multiplied by a factor of 5, and these two scores are summed to produce an aggregate, with total scores ranging from 8 to 66. For the current study, baseline SES ranged from 14 to 66 with an average of 40, such that on average, our sample is representative of lower middle class (Hollingshead, 1975).

Anthropometrics and BMI Trajectories

Lab measured height was collected to the nearest 0.1 cm using a measuring tape prior to 2015 (Graziano et al., 2013) and via stadiometer (SECA, Chino CA) with the initiation of RIGHT Track Health (Wideman et al., 2016). Similarly, weight was measured to the nearest 0.1 kg with an analog weight scale prior to 2015 (Graziano et al., 2013) and a balance-beam scale (Detecto-medic, Brooklyn NY) for the RIGHT Track Health study (Wideman et al., 2016). Height and weight data were used to compute BMI (kg/m^2) and baseline BMI percentile (%) was derived using a SAS macro produced by the Centers for Disease Control and Prevention (CDC). Longitudinal BMI measures and baseline demographics were used to derive a categorical variable to classify individuals into BMI trajectories.

Behavioral Data

This research utilizes data from two different laboratory tests as measures of self-regulation performed at age 4. Tests were modelled after those described in the Laboratory Temperament Assessment Battery (Lab-TAB) (Gagne et al., 2011; Goldsmith et al., 1995). The first task, a food-related task with snack delay, consisted of four separate trials which involved a researcher presenting a child with an M&M candy under a transparent glass jar, but making the child keep their hands on a place mat and wait an increasing amount of time (10, 20, 30, and 45 seconds) before allowing the child to eat the candy (Blandon et al., 2010; Kochanska, Murray, Jacques, Koenig, & Vandegeest, 1996). During this task, the researcher remained in the room standing beside the child for the full experiment time. For each trial, points were awarded based on the child's behavior. Children who waited until the bell was rung to touch or eat the treat received a minimum of 7 points, with possibility of two additional points for leaving their hands on the mat for the duration of the trial. Children who touched the glass, but not the candy, received at least 5 points, and those that touched or ate the snack during the trial received between 1 and 4 points. A total score of 36, corresponding to a maximum of 9 possible points for each trial, represents a perfect inhibitory control score (Spinrad, Eisenberg, & Gaertner, 2007). For ease of interpretation, a trichotomous variable was created corresponding to, regulated ($\geq$28) (i.e., child waited for the bell to be rung at a majority of trials before eating the candy, or at least 7 points at all 4 trials), moderately regulated ($\geq$ 20 but < 28) (i.e., child touched the glass, but did not

touch/eat the candy at a majority of trials, or at least 5 points at all 4 trials), and not regulated (<20) (i.e., child touched or ate the candy at a majority of trials).

The second task was a non-food tasks with gift delay. During this experiment, children were given a wrapped gift and instructed to not touch or open it until the researcher returned with a bow for the present (Graziano et al., 2010; Kochanska et al., 1996). Once presented with the gift box, researchers left the room and observed the child's behavior to determine the total time the child touched the gift, with total experiment time equaling three minutes. The proportion of time not touching the gift denotes levels of inhibitory control, with higher numbers resulting in better control. Due to limited variability in the non-food self-regulation variable, and for ease of interpretation, non-food self-regulation was dichotomized as regulated (not touching gift for ≥75% of the experiment) and non-regulated (not touching gift for <75% of the experiment) in a data-driven manner.

Statistical Analyses

A quadratic growth mixture model (GMM) was fit in Mplus version 8 to derive unique trajectories of BMI for individuals with at least two non-missing BMI measures (B. Muthen & Asparouhov, 2015; Nonnemaker et al., 2009). Bayesian Information Criteria (BIC) and the Lo-Mendell-Rubin likelihood ratio test (LMR LRT) were used to determine adequacy of model fit, with smaller BIC values and a significant LMR LRT p-value indicating better fit (B. Muthen, 2004; Nylund, Asparouhov, & Muthen, 2007). Entropy was also reported, where values greater than 0.8 support clear class delineation (Celeux & Soromenho, 1996; Tein et al., 2013). Time was centered at 11 years, the midpoint age of study participants, to reduce potential correlation between our linear and quadratic age terms (Raudenbush & Bryk, 2002).

A series of models were fit by constraining or freeing residual variance parameters for intercept (i), linear slope (s), and quadratic growth (q) and the best-fitting model was identified via previously mentioned criteria. Predictors of class membership, including race and socioeconomic status (SES), were identified by multinomial logistic regression and included into the best-fitting model to improve model performance and produce the final estimates for class membership (Isong et al., 2018). Additional details related to trajectory deviation have been discussed

previously (unpublished research, Chapter II). Children were classified into the class with the largest posterior probability from the best-fitting model (Magee et al., 2013).

Upon identification of the best-fitting model, SAS version 9.4 was used to produce descriptive statistics for each class and overall. A logistic regression model was used to assess the association between BMI trajectory membership and self-regulation behaviors (food and non-food tasks), controlling for sex, race, and baseline SES. Significance level used was alpha = 0.05.

Results

Two unique BMI trajectories were evident in our sample (Figure 3). Individuals in Class 1 (n=272), which includes most of our sample, were stable normal weight with BMI percentiles consistently between 5% and 85% (Figure 4). Although Class 2 (n=77) transitions from normal weight to obese to overweight status, on average, this transition was from normal weight to overweight (via BMI percentile above 85%). We used the following descriptors for classes 1 and 2 respectively: 1) stable normal weight and 2) normal weight to overweight transition.

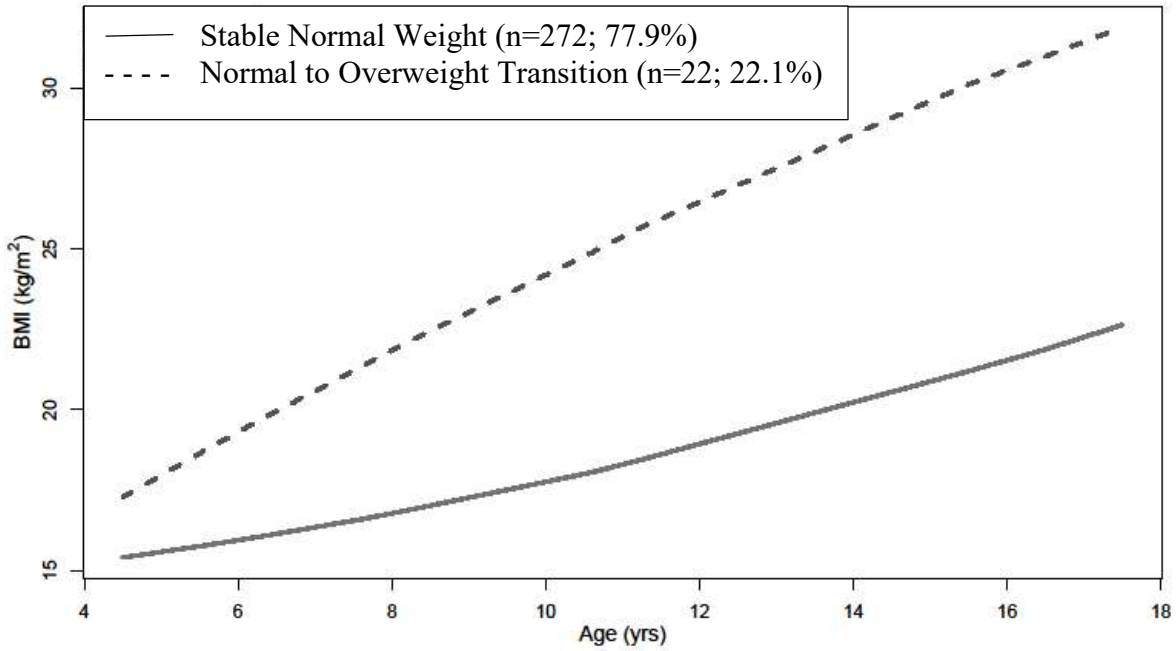

Figure 3. Longitudinal BMI Trajectories for Stable Normal Weight and Normal to Overweight Transition Groups

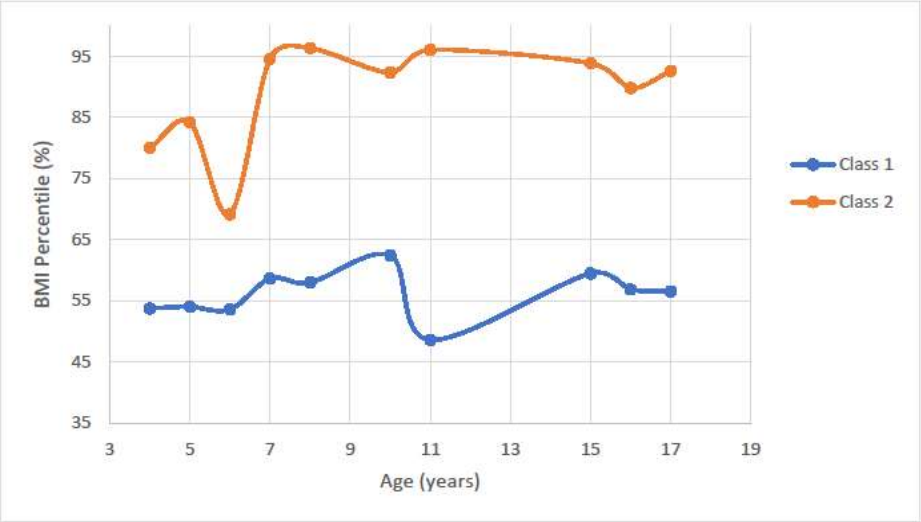

Figure 4. Average BMI percentile by BMI Trajectory Class Membership over Time

The stable normal weight class (Class 1) represented 78% of our sample and primarily consisted of Caucasian participants (71%). While both classes could be described as lower middle-class, with average SES values nearing 40 similar to the overall analytic sample, members of the transition class had lower SES as compared to the stable normal weight class (Hollingshead, 1975). As expected, average baseline BMI percentile was higher in the normal to overweight transition class as compared to the stable normal weight class.

The descriptive results related to self-regulation assessment in the food and non-food self-regulation tasks within each BMI trajectory membership are shown in Table 4. When considering levels of inhibitory control, the gift delay task showed that over 95% of our sample were regulated and were able to follow instructions and refrain from touching the gift provided to them. Similarly, the food-related snack delay task showed most of the sample was regulated. However, only approximately 86% of children were highly regulated based on the M&M task, with almost an additional 10% being identified as moderately regulated.

Table 4. Baseline Characteristics (4y) of Analysis Sample Overall and by BMI Trajectory Membership in the RIGHT Track Research Project (n=349)

	Overall	Stable Normal Weight	Overweight Transition	p-value[1]
n (%)	349	272 (77.9)	77 (22.1)	
Sex, n (%)				0.103
Male	160 (45.9)	131 (48.2)	29 (37.7)	
Female	189 (54.1)	141 (51.8)	48 (62.3)	
Race, n (%)				<0.001
Caucasian	229 (65.6)	194 (71.3)	35 (45.5)	
Non-Caucasian	120 (34.4)	78 (28.7)	42 (54.6)	
Food SR, n (%)				0.788
Not regulated	16 (5.1)	12 (4.7)	5 (5.5)	
Moderately regulated	31 (9.5)	26 (10.2)	5 (6.9)	
Regulated	281 (85.7)	217 (85.1)	64 (87.7)	
Non-Food SR, n (%)				<0.001
Not regulated	15 (4.6)	6 (2.4)	9 (12.3)	
Regulated	310 (95.4)	246 (97.6)	64 (87.7)	
Baseline BMI percentile, mean(std)	60.0(31.2)	54.2 (30.3)	80.0(25.5)	<0.001
SES, mean(std)	39.7(10.9)	40.8 (10.5)	35.9(11.6)	<0.001

[1]p-values from chi-square tests for frequencies and t-tests for means
BMI: body mass index; SES: socioeconomic status; SR: Self-regulation
Food SR Trial Score criteria: not regulated (<20); moderately regulated (20 to 27); regulated (≥28) (Spinrad et al., 2007)
Non-Food SR: not regulated (not touching gift for <75% of 3-minute experiment); Regulated (not touching gift for ≥75% of 3-minute experiment)

Table 5 provides results from the logistic regression analyses assessing associations of childhood self-regulation, baseline BMI percentile, and demographic variables with BMI trajectory membership. Regression analyses were conducted such that the lowest risk trajectory, stable normal weight, was the referent group. Non-Caucasian participants were significantly more likely than Caucasians to be in a higher risk BMI trajectory. Additionally, higher SES was associated with membership in a lower risk trajectory (i.e., Class 1). Further, higher levels of

self-regulation as measured by a non-food, gift delay task, was predictive of membership in the lower risk BMI trajectory. In contrast, self-regulation measured by a snack delay task was not associated with trajectory membership. Trajectory membership was not associated with sex.

Table 5. Association (Odds ratio† [95% Confidence Interval]) between Childhood Self-regulatory Behavior and Membership in a Normal to Overweight Transition Trajectory in the RIGHT Track Research Project (n=320)††

Variable	OR[95% CI]	p-value
Socioeconomic Status	0.97[0.95, 1.00]	0.048
Sex (Female)	1.59[0.88, 2.86]	0.124
Race (Non-Caucasian)	2.93[1.65, 5.20]	0.0002
Gift Delay (Regulated)	0.20[0.06, 0.63]	0.006
Snack Delay (3-cat)		
Moderately regulated vs not regulated	0.24[0.05, 1.27]	0.096
Regulated vs not regulated	0.56[0.15, 2.07]	0.383

OR, Odds Ratio; CI, Confidence Interval
† Odds ratio of membership in normal to overweight transition group versus stable normal weight group
†† Sample size of logistic regression model reduced due to missing covariates

Discussion

The purpose of this study was to determine if childhood self-regulation predicted BMI trajectories during childhood and adolescence. Our assessment of the relation between self-regulation at age 4 and BMI trajectories revealed that higher levels of inhibitory control measured by a non-food task were associated with lower odds of membership in the higher risk normal to overweight transition group. However, when measuring inhibitory control with a food-related task, the relation was not statistically significant. Previous investigations with food-related tasks have shown associations between better child self-regulation skills and lower BMI and/or adiposity among children (da Costa et al., 2019). Research conducted by da Costa et al assessed inhibitory control using both food and non-food related go no/go tasks, however, contrastingly to the present study, researchers found that food-assessed inhibitory control was significantly associated with weight status and non-food assessed inhibitory control had no significant association. However, da Costa et al assessed the relation between inhibitory control and weight status in a cross-sectional manner and used body fat instead of BMI patterns as their outcome (da Costa et al., 2019). Our non-significant findings for the food-related task could possibly be explained by the subtle variations in the methodologies that were utilized for the

food and non-food delay task measures in the Right TRACK study. For example, during the food-related task, a researcher stood beside the child for the full experiment time whereas the researcher left the room during the non-food task. Additionally, the child's parent/guardian was in the room during the non-food task. The presence of a non-parental authority figure could potentially have influenced child behavior in a different manner. Further, there are additional considerations with respect to the food-related task. Interest in food is individual; some participants may not have been tempted by the single M&M that was offered, or perhaps the child was not hungry. Moreover, the manner of assessment of the food-related task allowed for categorization of multiple levels of self-regulation by describing a regulated child as either having high regulation or moderate regulation.

Identifying modifiable childhood predictors of future health risk, such as BMI patterns, is becoming increasingly important. Research in laboratory settings have shown that food-specific interventions aimed at training a child's inhibitory control can decrease BMI (Allom & Mullan, 2015). We found that lower levels of childhood inhibitory control were associated with increased likelihood of transitioning from a normal to overweight BMI value. Our findings support existing research which has shown that lower levels of inhibitory control are associated with higher BMI values in children and adolescents. Cross-sectional research conducted in a sample of German children and adolescents aged 8 to 15 showed that low levels of inhibitory control, as measured by a go/no go laboratory task requiring participants to respond to a particular stimuli and to refrain from response in response to other stimuli, were associated with higher BMI measures (Pauli-Pott et al., 2010). Another study conducted in German primary school children demonstrated obese children were more likely to exhibit lack of inhibitory control, as compared to normal weight counterparts (Wirt et al., 2014). Similarly, a study of US adolescent lean and obese females used fMRI to assess brain regions associated with inhibitory control during a food-related go/no-go task (Batterink et al., 2010). Researchers found that subjects with higher BMI values exhibited lower inhibitory control in response to visual stimuli depicting desserts (Batterink et al., 2010). Further, research in a sample of Brazilian children aged 9 to 11 found that higher fat mass was associated with impaired food-related inhibitory control (da Costa et al., 2019).

While longitudinal analyses assessing future effects of childhood self-regulation are very limited in current literature, available studies have produced similar results to the current study showing that childhood self-regulation is linked to future weight status. Previous research in the RIGHT Track sample showed that poor self-regulation at age 2 was identified as a predictor of future risk of overweight at 5.5 y and 8 years later (Graziano et al., 2010; Graziano et al., 2013). Balantekin et al. explored the relation of childhood inhibitory control and adolescent BMI as related to female adolescent weight control behavior patterns (Balantekin et al., 2015). Females with the lowest levels of inhibitory control at age 7 had higher BMI values and were more likely to be extreme dieters in adolescence, whereas those with higher levels of childhood inhibitory control had lower BMI values and were more likely to have a healthier relation with food. Another longitudinal study in females showed that higher inhibitory control at age 7 was associated with smaller waist circumference and lower body fat percentage at both age 9 and age 15 (Anzman-Frasca et al., 2015).

This study was strengthened by its use of multiple methods to assess childhood inhibitory control, which allowed for the effects of food and non-food related inhibitory control to be parsed out. Many studies assessing inhibitory control use a variety of assessment methods including computer-based tasks (Batterink et al., 2010; Pauli-Pott et al., 2010), food-related go no/go tasks (Batterink et al., 2010; da Costa et al., 2019), LAB-TAB tasks involving toys or puzzles (Graziano et al., 2010), and parent-completed behavior surveys (Anzman-Frasca et al., 2015; Balantekin et al., 2015), however, to our knowledge, there are no existing studies that have examined the relation between early childhood inhibitory control measured by both food and non-food laboratory tasks, and BMI trajectories. This study was further strengthened by its longitudinal nature which provided information on long-term BMI trends rather than a single time point.

Despite the strengths of the study, there were several limitations that must be noted. The primary limitation of the current research is the limited sample size, however, the relation between childhood inhibitory control and future BMI trajectories was still evident in this sample. Another limitation was the minimal variability in the self-regulatory behavior variables at age 4 leading to the categorization of continuous self-regulation measures. While categorization provided the benefit of more easily interpretable results, it also has the potential for making it more

challenging to compare our results to studies that used continuous measures for food- and non-food inhibitory control. Future studies might explore self-regulation markers measured at later ages once self-regulatory behaviors have further developed and when corresponding assessment measures might have increased between subject variability. Additionally, exploration of food-related self-regulation measures at later ages could also provide more insight into the potential relations between moderation as it relates to food intake and BMI.

Conclusions

Obesity has many negative health implications and early identification of modifiable behaviors that are associated with future obesity can serve to greatly improve public health. The current study identified non-food related pre-school inhibitory control as a possible target for future interventions that may influence long-term BMI and potentially reduce future obesity-related health risks.

CHAPTER IV: DIETARY PATTERNS AND DIET QUALITY IN ADOLESCENCE AND THEIR ASSOCIATIONS WITH BIOMARKERS IN EARLY ADULTHOOD IN THE RIGHT TRACK HEALTH STUDY

This chapter is an article draft prepared for submission to the Journal of Nutrition.

Abstract

Background: Dietary patterns characterized by high consumption of processed and fried foods have been associated with increased metabolic risk as early as adolescence. Risk factors in early life have the potential to influence health during adulthood, and so early identification of modifiable behaviors that can reduce metabolic risk has the potential to greatly impact long term health.

Objective: To derive dietary patterns in adolescence and assess their association with anthropometrics and cardiometabolic biomarkers collected in emerging adulthood.

Methods: Latent class analysis (LCA) on 21 food groups was used to derive dietary patterns using 24-hr dietary recalls from a sample of adolescents (n=148) in the RIGHT Track Health Studies (1996-2021). Multiple linear regression was used to assess the relations between adolescent dietary patterns with early adulthood anthropometrics and biomarkers (fasting glucose, fasting insulin, HOMA-IR) adjusting for sex, race, and socioeconomic status.

Results: LCA identified two distinct dietary patterns: balanced (characterized by higher consumption of unsweetened beverages, fruits, and non-starchy vegetables) and unbalanced (characterized by greater consumption of sugar-sweetened beverages, fried potatoes, and full fat/fried meats). Both patterns had similar consumption of refined grains and sweet snacks, with over half of each class being “high” consumers. No significant associations were found between adolescent dietary patterns and any early adulthood biomarker or anthropometric measure. While average diet quality, as assessed by HEI scores, was significantly higher for the balanced pattern

as compared to the unbalanced pattern, HEI scores were considered poor for both dietary patterns (HEI < 59) indicating poor adherence to the current Dietary Guidelines for Americans.

Conclusion: Diet quality of adolescents in our sample was poor regardless of dietary pattern. Balanced and unbalanced patterns were both characterized by high intake of refined grains and sweets, suggesting that interventions promoting reduced intake of these foods in favor of increased intake of more nutrient dense foods may help improve diet quality for a larger number of adolescents.

Introduction

Adolescence is an important developmental period during which many hormonal changes occur, and lifestyle habits associated with physical and mental health are established (Agirbasli, Tanrikulu, & Berenson, 2016). Many of these lifestyle habits, such as dietary intake, are associated with increased disease risk (Cunha et al., 2018; Iannotti & Wang, 2013b; Shrestha & Copenhaver, 2015). Risk factors in early life have the potential to influence health during adulthood (Shrestha & Copenhaver, 2015), and so early identification of modifiable behaviors that can reduce metabolic risk has the potential to greatly impact long term health.

Biomarkers are biological measurements that can be used in research and clinical settings to not only diagnose particular disease states, but can additionally provide insight into future disease risk (Choong & Tsafnat, 2012). Insulin resistance has been identified as an important cardiovascular risk factor (Adeva-Andany et al., 2019) and fasting glucose, fasting insulin, and Homeostatic Model Assessment of Insulin Resistance (HOMA-IR) are the primary biomarkers used to identify individuals with insulin resistance (Singh & Saxena, 2010), which can be a first step in the development of cardiovascular disease (Ginsberg, 2000). Fasting glucose levels at or above 126 mg/dl on at least two separate occasions, or a glucose value of at least 200 mg/dl at any single measurement, are the current standard for diagnosis of diabetes (Gedela et al., 2007), however, measuring insulin levels can identify insulin resistance prior to clinical signs of metabolic disease (Singh & Saxena, 2010). Thus, collecting data on insulin values, in addition to glucose and HOMA-IR levels, serve to provide estimates on beta-cell function and insulin resistance (Singh & Saxena, 2010). In addition to biomarkers, measures of body shape and body composition have been shown to be associated with metabolic functioning (Lee et al., 2006).

Waist circumference, as a proxy for abdominal fatness, has been shown to relate to insulin sensitivity in children, with larger waist circumferences being associated with decreased insulin sensitivity (Lee et al., 2006). Further, body composition, as assessed by percentage of body fat, has association with HOMA-IR in adolescent populations (Wedin et al., 2012).

Dietary intake is a modifiable behavior that has been associated with obesity and increased risk of cardiovascular disease (Cunha et al., 2018; Iannotti & Wang, 2013b). Previous studies in adults have established links between certain dietary patterns and metabolic risk factors, including higher BMI, adiposity, HOMA-IR and fasting glucose (Rocha et al., 2017). Results in adolescents have shown that diets higher in sugar-sweetened beverages and fast food are associated with increased risk of obesity (Moreno et al., 2010). Adolescence is a critical developmental period during which individuals are becoming increasingly influenced by external influences (Moreno et al., 2010). Adolescents are beginning to have more independence and are able to make more decisions on what they eat (Moreno et al., 2010). This independence often leads to an increased number of meals eaten with peers outside of the home, with these meals typically including fast food meals and sugar-sweetened beverages (Moreno et al., 2010; Ruiz, Zuelch, Dimitratos, & Scherr, 2019). Dietary intake of processed and fried foods has been associated with obesity as early as adolescence. Of note, prevalence of cardiovascular disease risk factors such as hypertension and elevated glucose levels are higher in overweight and obese individuals (Saydah et al., 2014). Further, obese adolescents have higher risk of insulin resistance and hyperglycemia (Ruiz et al., 2019).

Many existing analyses of diet in children and adolescents rely on assessment of specific food groups or nutrients (i.e., sugar sweetened beverages; saturated fat intake) or pre-specified dietary indices, such as the Healthy Eating Index (HEI) or Dietary Approaches to Stop Hypertension (DASH) scores, which use the sum of scores for intake of individual food components to determine an overall score (Berz et al., 2011; Costacou et al., 2018). High diet quality measured by these indices has been associated with decreased risk of cardiovascular disease and type 2 diabetes in adults (Schwingshackl et al., 2018), however, research in adolescents has shown that there is limited variation in diet quality in this population, with most having low diet quality (Winpenny, Greenslade, Corder, & van Sluijs, 2018). In populations with similar diet quality, diet-quality indices often produce homogeneous scores. Thus, these scores

are not useful for identification of groups with unique dietary patterns since individuals with similar diet-quality scores may consume different types of food (NCI). Dietary patterns describe overall diet in terms of the quantity and combinations of foods individuals most habitually consume, rather than a single nutrient (Cespedes & Hu, 2015; F. B. Hu, 2002). Dietary patterns allow researchers to better understand how overall dietary intake may vary in populations with similar diet quality and can better describe how overall diet may be associated with health outcomes, rather than being limited to studying single food or nutrient relations (Rocha et al., 2017). Further, the 2020-2025 Dietary Guidelines for Americans now focus on the importance of dietary patterns, as it is the synergistic effects of foods that influence health (U.S. Department of Agriculture and U.S. Department of Health and Human Services).

Dietary patterns characterized by high consumption of processed and fried foods have been associated with increased metabolic risk in adolescents cross-sectionally (Ambrosini et al., 2010). However, the relation between adolescent dietary intake and adult health markers has been less explored. Glucose dysregulation, as a marker of cardiovascular risk, is becoming prevalent earlier in life (Giannini et al., 2012) with substantial decline in pancreatic beta cell function being seen up to 15 years prior to a diabetes diagnosis (Levy, Atkinson, Bell, McCance, & Hadden, 1998). As such, emerging adulthood, a developmental period during 18 to 25 years (Nelson et al., 2008), is becoming of greater interest since changes in health outcomes can be seen and this developmental period provides an additional opportunity for behavior change interventions (Gilmore, 2019). Thus, the main purpose of the current longitudinal study was to describe the relation between dietary patterns in adolescents and selected markers during emerging adulthood that are known to be related to cardiometabolic health.

Methods

Data for the current study were collected as part of the Research Investigating Growth and Health Trajectories (RIGHT) Track and RIGHT Track Health longitudinal studies (Wideman et al., 2016). The RIGHT Track study was designed to examine developmental changes in social, emotional, and physical health from childhood to adolescence and the RIGHT Track Health study has built upon the original study by examining self-regulation in relation to cardiometabolic risk through early adulthood. Participants (n=447) were followed from 2 years of age through emerging adulthood, with final data collected during laboratory visits between 18

and 25 years of age. Subjects were recruited during 1994-1996 via program services such as day care centers, County Health Departments, and Women, Infants, and Children (WIC) services in central North Carolina and were representative of the surrounding community in terms of race and socioeconomic status (SES). The baseline study population included three cohorts of children, with approximately 37% of the sample being considered at risk for future behavioral issues (Wideman et al., 2016). There were no significant demographic differences between cohorts with respect to gender, race, or baseline SES. Additional details of the RIGHT Track Health study design and sample are provided in Wideman et al. (Wideman et al., 2016).

STUDY MEASURES AND VARIABLES

Height was collected by stadiometer to the nearest 0.1cm (SECA, Chino CA), weight was measured via balance-beam scale to the nearest 0.1 kg (Detecto-medic, Brooklyn NY), and corresponding BMI (kg/m^2) was computed (Wideman et al., 2016). Waist circumference (WC) was measured at the natural waist to the nearest 0.1 cm using a Gulick tension-tape measure(Wideman et al., 2016). Percent body fat measured via BODPOD following a daily calibration protocol (Cosmed, Concord, CA, USA).

Fasting serum glucose (mg/dl) and fasting serum insulin (pg/ml) were obtained using colorimetric assay (Caymen Chemical, Ann Arbor, MI) at two time points during emerging adulthood (18y – 23y) (VanKim, Larson, & Laska, 2012; Wideman et al., 2016). Insulin was converted from pg/mL to g/mL by a factor of 10^{-3} and g/mL to µIU/mL via a factor of 28.8. Insulin values were reported in both µIU/mL and pmol/L for ease of comparison to other studies. As such, µIU/mL was converted to pmol/L via a factor of 6.00 as recommended in previous research (Knopp et al., 2019). Homeostatic Model Assessment for Insulin Resistance (HOMA-IR), a measure of insulin resistance, was computed via fasting insulin (µIU/mL) x fasting glucose (mg/dl)]/405 (Rivas-Crespo, 2015). To minimize missing data, the earliest of the two time points for which the participant's non-missing adult biomarker data were available (i.e., $\geq$ 18 years) was used in analyses, with HOMA-IR only being computed if FPG and FPI were available at the same visit.

Dietary intake data were collected for a subset of RIGHT Track Health participants during adolescents by the Nutrition Obesity Research Center (NORC) at the University of North

Carolina Chapel Hill via 24-hr dietary recalls using Nutrition Data System for Research (NDSR) software developed by the Nutrition Coordinating Center (NCC), University of Minnesota, Minneapolis, MN. To reflect the marketplace throughout the study, nutrient composition was computed using the most updated NDSR version available during each dietary data collection year (i.e., 2013, 2014, 2015, 2016, and 2017). The NDSR time-related database updates analytic data, while maintaining nutrient profiles true to the version used for data collection.

Three dietary recalls (2 weekdays and 1 weekend day) were collected for each participant between ages 16 and 18 (n=148). Dietary intake reports generated by the NDSR included 168 food items, corresponding to nine major food groups (Appendix B1). Food items not consumed by any participant at any time point were excluded (n=26). The remaining food items (n=142) were collapsed into 21 food categories using the USDA's Food Patterns Equivalents Database 2015-2016 (FPED) as a reference (Bowman, Clemens, Shimizu, Friday, & Moshfegh, 2018). In the interest of distinguishing between snack foods low in nutrient density and more nutrient dense grain-based foods, the primary grain categories provided by the FPED, whole grains and refined grains, were expanded to include snacks. Additionally, a dessert category was added since the FPED summarizes this under a more generic 'added sugars' category. A full list of food items, food groups, and food categories are provided in Appendix B1; excluded food items are also provided.

Since distributions of food servings were left skewed due to high non-consumption of certain food categories, ordinal intake variables were derived. Standardized median servings (median servings per 1000 kilocalories) were computed for consumers of each of the 21 collapsed food categories. Standardized medians were then rounded to the nearest 0.25 serving to create cut points that allow for easier comparison to standard serving sizes. Highly consumed food categories (<10% non-consumers) were dichotomized at their respective cut point (i.e., highly consumed vs. low or non-consumed). Food categories with low consumption (>70% non-consumers) were dichotomized as consumed or non-consumed. Remaining food categories were categorized as non-consumed, consumed below cut point (i.e., low consumed), and consumed above cut point (i.e., highly consumed) (Martin et al., 2016). Standardized medians, cut points, and categorical consumption percentages for each food category are summarized in Table 6.

Sex, race, and Hollingshead index of SES (Hollingshead, 1975) at age 2 were used as covariates in analyses. Due to the small sample size in non-White race categories, race was dichotomized as 'Caucasian' and 'non-Caucasian' (African American, biracial, and other). In the RIGHT Track sample, SES at age 2 ranged from 40 to 54, reflecting minor professional and technical occupations considered to be representative of middle class (Hollingshead, 1975).

Statistical Analyses

Multiple computing software programs were used to complete statistical analyses. Latent class models were fit using Mplus version 8.0 and multiple linear regression analyses were performed using SAS version 9.4. Latent class analysis (LCA) was used to derive unique dietary patterns using standardized categorical consumption variables in models with 1 to 4 classes. LCA models grouped participants into mutually exclusive classes based on their highest posterior probability (Masyn, 2013). The Bayesian Information Criterion (BIC) and parametric bootstrapped likelihood ratio test (B-LRT) were used for model selection due to our small sample size (Nylund et al., 2007), and entropy and Lo-Mendell-Rubin (LMR) values were also reported.

Multiple linear regression models were fit to assess separately the relationship between adolescent dietary pattern and adult measures of BMI, percent body fat, FPG, FPI, and HOMA-IR adjusting by sex, race, and SES. Outcomes were transformed as needed to meet normality and homoscedasticity assumptions and outliers were capped at the 1st and 99th percentiles

Results

The LCA of dietary patterns showed that the 2-class model had the smallest BIC and had a significant p-value for the B-LRT, indicating the 2-class model was a better fit as compared to the 1, 3, and 4-class models (Table 2). These two distinct classes were labeled as "balanced" (n=62) and "unbalanced' (n=86) dietary patterns.

The balanced pattern was characterized by high consumption of unsweetened beverages, reduced fat dairy and dairy substitutes, fruits, whole grains, non-starchy vegetables, and vegetable protein, and consumption of these food groups was significantly higher in the balanced as compared to the unbalanced pattern. The unbalanced pattern was characterized by high consumption of fried vegetables, full fat/fried/cured meats, sugar-sweetened beverages, and

refined grains even though this did not differ from individuals following the balanced pattern. Figures 5 to 7 display the probabilities of consumption of food groups by dietary pattern.

There were no differences in age, baseline SES, or adult waist circumference when comparing the balanced and unbalanced dietary patterns. However, a larger percentage of females and Caucasians followed the balanced pattern as compared to the unbalanced pattern (Table 8). In terms of dietary quality, those following the unbalanced pattern had a lower HEI score (d=-8.3) and consumed significantly higher daily calories as compared to those in the balanced pattern (d=372.6 kcal/day), with this relationship holding after adjustment for sex and race. On average, individuals in the balanced pattern had HEI scores near 53 while those in the unbalanced pattern had a lower average score of 46. No difference was seen in the percent of total kilocalories from carbohydrates between the two patterns, and while differences in percent calories from protein and fat were attenuated after adjustment for sex and race, they remained significant. Of note, percent of calories from macronutrients were within recommended ranges for both balanced and unbalanced patterns (i.e., % calories from protein (10-30%), fat (25-35%), and carbohydrates (45-65%) for male and female adolescents) (U.S. Department of Agriculture and U.S. Department of Health and Human Services). Furthermore, dietary pattern membership and diet quality in adolescence had no association with early adulthood BMI, percent body fat, fasting glucose, fasting insulin, or HOMA-IR (Tables 9 and 10).

Discussion

The main purpose of the study was to identify dietary patterns consumed in adolescence and determine associations of adolescent dietary intake and diet quality with markers of cardiometabolic risk during emerging adulthood. We identified two unique patterns of adolescent dietary intake in the RIGHT Track Studies: balanced and unbalanced. While both patterns had similar consumption of sweet snacks, starchy vegetables, fats, and full fat dairy, adolescents with the balanced pattern had higher intakes of non-starchy vegetables, fruits, whole grains, unsweetened beverages, and reduced-fat dairy products as compared to the adolescents with the unbalanced pattern. Further, while not statistically significant, participants in the balanced pattern consumed more lean protein sources as compared to the unbalanced pattern. Contrastingly, the unbalanced pattern was characterized by increased intake of sugar-sweetened beverages, fried vegetables, and fatty and cured meats, although none were statistically different

from the balanced pattern likely due to the large variability in consumption of these food categories.

Previous research suggests that diets higher in fast food, sugar-sweetened beverages, and candies are associated with increased cardiometabolic risk including larger average waist circumference, and higher BMI and blood glucose levels (Cunha et al., 2018). In the current study, adolescent dietary pattern was not associated with adult BMI, adiposity (% of body fat) or any of the metabolic markers measured in early adulthood after adjustment for race, sex, and socioeconomic status. Despite the differences in patterns of dietary consumption, the average diet quality as measured by HEI was significantly higher for the balanced pattern as compared to the unbalanced pattern. However, average HEI scores for both patterns fell below 59, indicating poor diet quality for both dietary patterns. Adjusted models assessing the relation between adolescent diet quality and adult BMI and metabolic markers were nonsignificant.

Our findings are in line with the existing, yet limited, literature in that a majority of research in child and adolescent populations has identified two patterns of dietary intake (Cunha et al., 2018). Of the 19 studies outlined in a meta-analysis by Cunha et al, all but one study reported two distinct dietary patterns in children and adolescents under the age of 19. While the studies summarized by Cunha et al. defined dietary patterns in various ways, most studies reported at least one 'unhealthy' dietary pattern and one 'healthy' pattern (Cunha et al., 2018). 'Unhealthy' patterns included foods such as pizza, processed and high fat meats, and sugar-sweetened beverages and desserts (Cunha et al., 2018), and were most often referred to as a 'Western diet' (Ambrosini et al., 2010; Bahreynian, Paknahad, & Maracy, 2013; Gutierrez-Pliego et al., 2016). 'Healthy' patterns varied in the types of foods represented, but most often included foods such as whole grains, legumes, fruits, and vegetables (Cunha et al., 2018). These 'healthy' patterns were characterized in many different ways (Cunha et al., 2018) and included descriptive terms such as "healthy," (Ambrosini et al., 2010; Bahreini Esfahani et al., 2016) "prudent," (Gutierrez-Pliego et al., 2016; Hojhabrimanesh et al., 2017) and "traditional" (Song, Joung, Engelhardt, Yoo, & Paik, 2005; Weng et al., 2012).

While one of the main goals of this research was to refrain from categorizing a particular pattern as 'healthy' or 'unhealthy,' the balanced pattern identified in the current study can be most

closely compared to the 'healthy' patterns, and the unbalanced pattern most closely compared to the 'unhealthy' patterns described above in terms of highly consumed food categories. However, it is important to note that both balanced and unbalanced patterns were marked by high consumption of foods such as refined grain and sweet snacks, with previous studies having classified these foods into 'unhealthy' patterns (Ambrosini et al., 2010; Gutierrez-Pliego et al., 2016). Further, both of the dietary patterns identified in this study had average HEI scores below 59, which is the cut point associated with very poor adherence to the dietary recommendations outlined in the Dietary Guidelines for Americans (Krebs-Smith et al., 2018).

The studies described in Cunha et al. utilized factor, cluster, or principal component analysis (PCA) for derivation of dietary patterns (Cunha et al., 2018) rather than the LCA methodology utilized in the current study. While factor, cluster or PCA methods are extremely useful at identifying foods most likely to be eaten in combination (i.e., correlated food items) (Bertin et al., 2016; LeCroy et al., 2019; Maia et al., 2018; Togo et al., 2003; J. Zhang et al., 2015), LCA classifies individuals into mutually exclusive groups with similar food consumption (Iannotti & Wang, 2013a; Sotres-Alvarez et al., 2010). This difference in methodology can possibly explain why the two dietary patterns identified in this research both have high consumption of foods that previous research only attributed to diets with overall lower quality. An advantage of the LCA methods utilized in this study over the formerly identified methods is that LCA identifies groups of individuals with unique dietary intake (Sotres-Alvarez et al., 2010). As such, the risk of a particular outcome can then be estimated and compared for each identified group (Sotres-Alvarez et al., 2010), which was the primary aim of the existing study.

Contrary to the current study, previous studies have established links between dietary patterns high in processed food and fat and metabolic risk factors, including higher adiposity, higher levels of insulin resistance, as measured by HOMA-IR, and fasting glucose in childhood and adolescence (Rocha et al., 2017). A study in Chinese children and adolescents conducted by Zhang et al. found that dietary patterns characterized by increased intake of fast food and simple carbohydrates were associated with increased risk of obesity (J. Zhang et al., 2015). In the meta-analysis by Cunha et al., consumption of 'unhealthy' dietary patterns was associated with increased BMI and waist circumference (Cunha et al., 2018). Research in a sample of Mexican adolescents identified three dietary patterns corresponding to westernized, prudent, and high

protein/high fat diets, with the westernized and high protein/fat patterns being correlated with higher BMI values (Gutierrez-Pliego et al., 2016). However, these assessed studies were cross-sectional and as such, they did not evaluate the relations between dietary intake in childhood and adolescence and future health markers as in the current study (Cunha et al., 2018; Gutierrez-Pliego et al., 2016; Rocha et al., 2017; J. Zhang et al., 2015). Although Wright et al. described the relation between adult BMI and longitudinal patterns of protein intake from childhood to adulthood (Wright et al., 2017), the current study provides one of the few contributions describing the relation between dietary patterns in adolescence and adult biomarkers.

The main assumption for this study is that dietary patterns are stable over time such that future health effects would be related to a consistent dietary pattern over an increased duration. While stability of dietary patterns has been shown in young adult women (Borland, Robinson, Crozier, Inskip, & Group, 2008), it is likely that adolescent diet is not stable over time. In our sample, dietary changes were evident for individuals that had dietary intake data during both adolescence and adulthood. The transition from adolescence to emerging adulthood comes with many changes, in particular the change from being dependent on parents for food and shelter to becoming more financially and socially independent (Arnett, 2000; Gilmore, 2019), and these changes can influence dietary intake. While consumption of fruits, vegetables, and sweets were relatively stable over time, in our sample the transition to adulthood resulted in increased intake of alcohol, reduced fat dairy, and unsweetened beverages and a corresponding decrease in reduced fat dairy and sugar-sweetened beverages, as well as decreased consumption of refined grains. However, these data were only available for a subset of individuals (n=111) and may not accurately reflect longitudinal changes in dietary patterns for the full sample. Another limitation was our small sample size. Dietary data were only collected for a subset of participants, and adult biomarker data were only available for about one-third of those with complete dietary data.

A major strength of this study was its longitudinal nature, which allowed the study to contribute to the existing literature by exploring how adolescent diet may impact future health markers. Further dietary intake was assessed via 24-h recalls by trained staff using a multiple pass approach (Wideman et al., 2016). Additionally, three dietary recalls, on both weekdays and weekend days, were collected for each participant. Dietary data collected by 24-h recalls is considered the gold standard for estimating energy intake (Ma et al., 2009) and collection of

multiple interviews on various days is necessary to obtain a reliable estimate of a person's habitual dietary intake (Looman et al., 2019). This study also utilized latent class methodology for identification of dietary patterns rather than factor and principal component analyses, which allowed for comparison of health outcomes for individuals with unique dietary intake.

Conclusion

While our study found no association between adolescent dietary intake and adult measures of cardiometabolic health, this study showed that diet quality in our sample was poor regardless of dietary pattern (HEI < 59) (Krebs-Smith et al., 2018). Even though the diet quality of the balanced pattern was higher than the unbalanced pattern, both patterns were characterized by increased intake of refined grains and sweets. Given the similar intake of these foods, behavioral modification interventions that target these food categories may have the potential to improve the diet quality of a larger number of adolescents.

Table 6. Median Food Group Consumption (Unstandardized and Standardized), Final Cut Points, and Consumption Distribution (n=148)[1, 2]

Food Group	Median servings/ day	Standardized Median servings (per 1000 kcal)	Cut point	Non-consumers (%)	Consumers below cut point (%)	Consumers at/above cut point (%)
Sugar-Sweetened Beverages	1.67	0.88	1.00	19.6	43.9	36.5
Reduced and Noncaloric Beverages[3]	3.36	1.98	2.00	4.0	48.7	47.3
Alcoholic Beverages[4]	0.04	0.03	0.00	96.6	N/A	3.4
Full Fat Dairy[3]	0.42	0.25	0.25	7.4	46.0	46.6
Reduced/Fat Free Dairy[3]	0.90	0.48	0.50	9.5	47.3	43.2
Non-Dairy Substitutes[5]	0.33	0.21	0.25	83.1	9.5	7.4
Full Fats[3]	1.73	0.99	1.00	0.7	50.0	49.3
Reduced Fats	0.55	0.28	0.25	58.8	18.9	22.3
Fruits	0.67	0.35	0.25	42.6	20.3	37.1
Fruit Juice	0.67	0.40	0.50	60.8	21.6	17.6
Whole Grains and Starches	1.27	0.66	0.75	27.0	44.6	28.4
Refined Grains[3]	4.30	2.52	2.50	0.0	49.3	50.7
Snacks	0.85	0.48	0.50	34.5	33.8	31.7
Desserts[3]	1.14	0.65	0.75	6.0	56.8	37.2
Starchy Vegetables[5,6]	0.23	0.15	0.25	40.5	36.5	23.0
Non-Starchy Vegetables[3]	0.93	0.57	0.50	1.4	43.9	54.7
Fried Vegetables[7]	0.74	0.38	0.50	44.6	33.8	21.6
Vegetable Protein	0.67	0.43	0.50	48.6	29.7	21.6
Lean Meats[3]	2.00	1.19	1.25	4.1	52.0	43.9
Full Fat, Fried, and Cured Meats[3]	2.47	1.36	1.25	8.8	41.9	49.3
Condiments/Other[3]	0.81	0.48	0.50	13.5	43.9	42.6

[1] For those with at least 3 dietary recalls during adolescence

[2] Table with all 142 food items and corresponding NDSR variable codes is available in Appendix B1

[3] Non-consumers and consumers below cut point merged to form dichotomous consumption variable for latent class analysis

[4] Consumers below cut point and consumers above cut point merged to form dichotomous consumption variable for latent class analysis
[5] Consumers below cut point and consumers at/above cut point merged to form dichotomous consumption variable latent class analysis
[6] Excludes fried potatoes
[7] Includes fried potatoes

Table 7. Model-fit Results of Latent Class Analysis for Derivation of Dietary Patterns for Participants with Three Dietary Recalls in Adolescence (n=148)

# Classes	BIC	Entropy	LMR p-value	B-LRT p-value
1	5223.3	N/A	N/A	N/A
2	5217.5	0.797	0.033	0.000
3	5304.4	0.870	0.946	0.150
4	5391.2	0.918	0.782	0.150

BIC: Bayesian Information Criterion; LMR: Lo-Mendell-Rubin Likelihood Ratio Test; B-LRT: Bootstrapped likelihood ratio test

Table 8. Sociodemographic Characteristics, Adolescent Macronutrient Intake and Diet Quality, and Early Adulthood Waist Circumference by Dietary Pattern[1]

Characteristic	Balanced Pattern n=62	Unbalanced Pattern n=86	p-value[2]
Age[3] at Dietary Recall (y), mean ± SD	16.8 ± 0.5	16.8 ± 0.4	0.427
Race, % Caucasian	80.7	50.0	<0.001
Sex, % male	27.4	48.8	0.01
SES[4], mean ± SD	40.8 ± 10.6	39.2 ± 10.9	0.398
Energy Consumption (kcal/d), median (IQR)			
median (IQR)	1475.1 (605.2)	1847.7 (838.3)	<0.001
adjusted median[5] ± SD	1532.0 ± 73.8	1999.5 ± 69.6	<0.001
Protein (% kcal), median (IQR)			
median (IQR)	17.0 (5.7)	15.0 (4.8)	0.001
adjusted median[5] ± SD	17.7 ± 0.6	15.2 ± 0.4	0.001
Fat (% kcal), mean ± SD			
mean ± SD	32.2 ± 5.2	34.5 ± 5.3	0.009
adjusted mean[6] ± SD	32.6 ± 0.7	34.5 ± 0.6	0.034
Carbohydrates (% kcal), mean ± SD			
mean ± SD	50.2 ± 6.5	50.2 ± 7.4	0.950
adjusted mean[5] ± SD	49.7 ± 0.9	50.2 ± 0.8	0.679
HEI 2015 Total Score, mean + SD			
mean ± SD	53.5 ± 11.1	45.2 ± 9.2	<0.001
adjusted mean[5] ± SD	53.1 ± 1.4	45.0 ± 1.0	<0.001
Waist Circumference (cm), mean ± SD			
mean ± SD	80.5 ± 17.3	82.3 ± 15.0	0.501
adjusted mean[5] ± SD	82.1 ± 2.9	82.8 ± 1.9	0.828

HEI: Healthy Eating Index

[1] Results are means ± SD for normally distributed continuous variables, medians (interquartile range) for skewed continuous variables, and percent for categorical variables.

[2] t-test for continuous means, Wilcoxon rank sum test for continuous medians, Wald test for adjusted medians, ANOVA for adjusted means, and Fisher's Exact test for proportions.

[3] Average age across all three dietary recalls.

[4] Hollingshead score for socioeconomic status at age 2.

[5] Adjusted by age at dietary recall, sex, and race.

Table 9. Association (regression coefficient and 95% CI) between Adolescence Dietary Pattern and Early Adulthood Adiposity and Biomarkers[1]

	BMI (n=116)		% BF (n=102)		Fasting Glucose[2] (n=107)		Fasting Insulin[2] (n=102)		HOMA-IR[2] (n=101)	
Parameter	b(95%CI)	p-value	b(95%CI)	p-value	b(95%CI)	p-value	b(95%CI)	p-value	b(95%CI)	p-value
Unbalanced Dietary Pattern (ref=Balanced)	-0.97 (-3.47,1.53)	0.444	0.61(-3.62,4.84)	0.775	5.11(-1.51, 11.74)	0.129	-2.08 (-36.25, 32.09)	0.904	4.78 (-30.02, 39.59)	0.786

BMI: Body Mass Index (kg/m^2); %BF: Body fat percentage; HOMA-IR: Homeostatic Model Assessment for Insulin Resistance

[1] All models adjusted for race, sex, socioeconomic status.

[2] Since Fasting Glucose, Fasting Insulin, and HOMA-IR were natural log transformed, corresponding regression coefficients were multiplied by 100 and interpreted as the percentage of change in the outcome for being in the Unbalanced class compared to the referent Balanced class

Table 10. Association (regression coefficient) between Adolescence Dietary Quality and Early Adulthood Adiposity and Biomarkers[1]

	BMI (n=116)		% BF (n=102)		Fasting Glucose[2] (n=107)		Fasting Insulin[2] (n=102)		HOMA-IR[2] (n=101)	
Parameter	b(95%CI)	p-value	b(95%CI)	p-value	b(95%CI)	p-value	b(95%CI)	p-value	b(95%CI)	p-value
HEI 2015	-0.08 (-0.18, 0.03)	0.170	-0.11 (-0.29, 0.06)	0.211	0.99 (0.996, 1.002)	0.632	1.001 (1.01, 1.02)	0.861	1.002 (0.99, 1.02)	0.806

BMI: Body Mass Index (kg/m^2); %BF: Body fat percentage; HOMA-IR: Homeostatic Model Assessment for Insulin Resistance

[1] All models adjusted for race, sex, socioeconomic status.

[2] Since fasting Glucose, Fasting Insulin, and HOMA-IR were natural log transformed, corresponding regression coefficients were exponentiated and interpreted as the change in a one-unit increase of the non-transformed outcome.

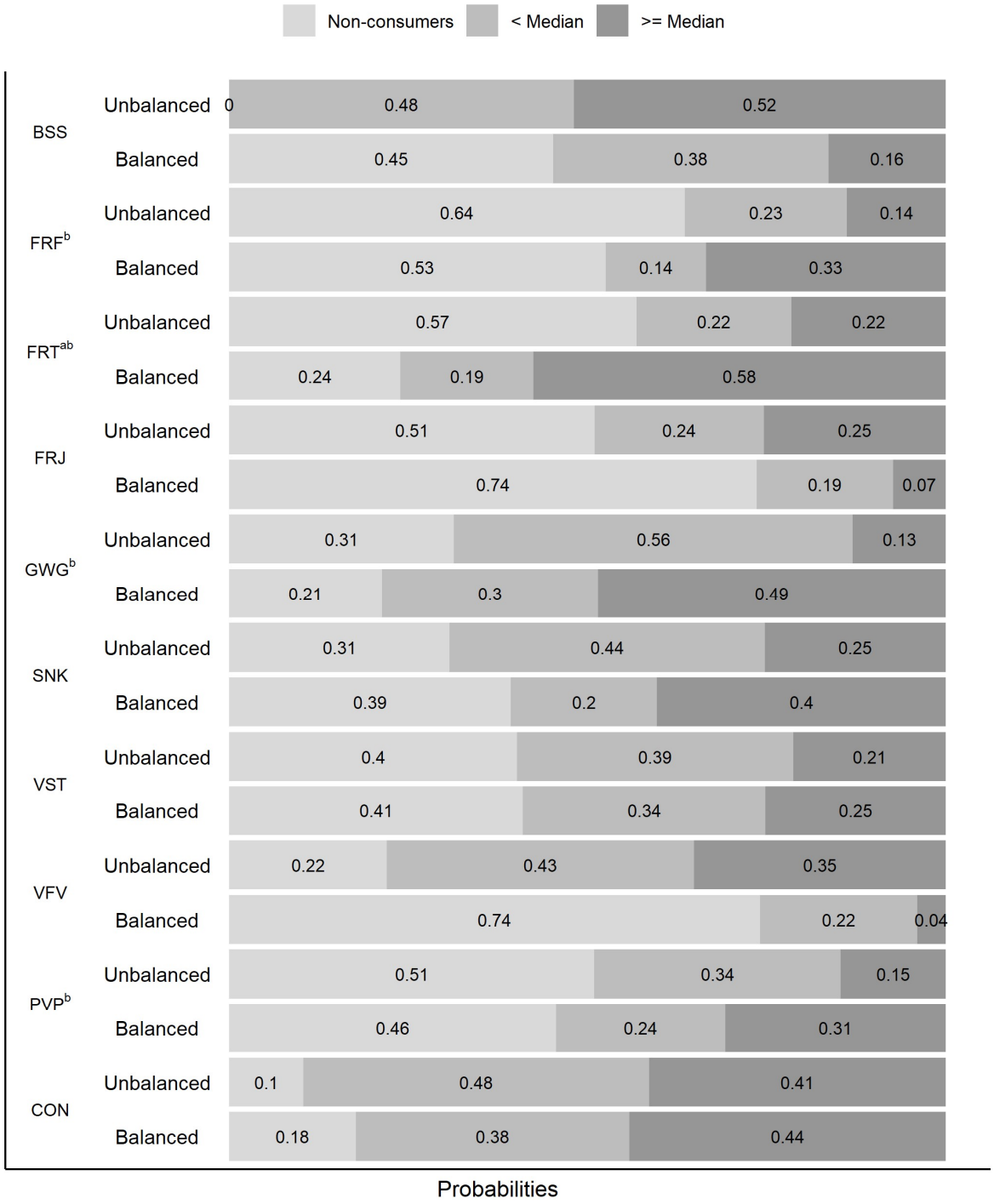

Figure 5. Probabilities of Consumption of 3-Level Ordinal Food Groups by Dietary Pattern

[a] Significant odds ratio for Unbalanced vs. Balanced comparing high + low consumption to non-consumption ($p<0.05$); [b] Significant odds ratio for Unbalanced vs. Balanced comparing high consumption to non+low consumption ($p<0.05$)

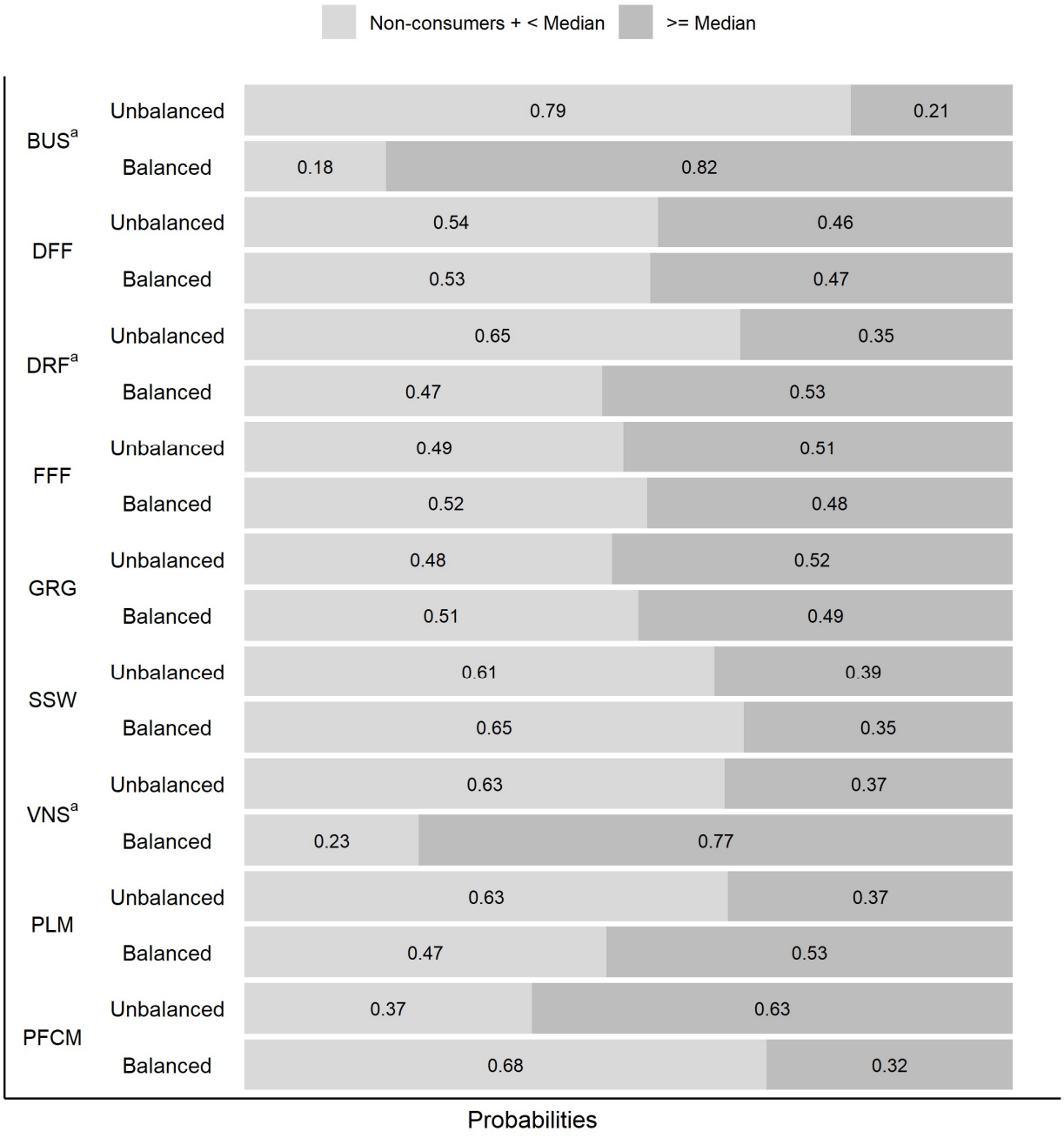

Figure 6. Probabilities of Consumption of High versus Low Dichotomous Food Categories by Dietary Pattern

[a] Significant odds ratio for Unbalanced vs. Balanced comparing high consumption to non+low consumption ($p<0.05$)

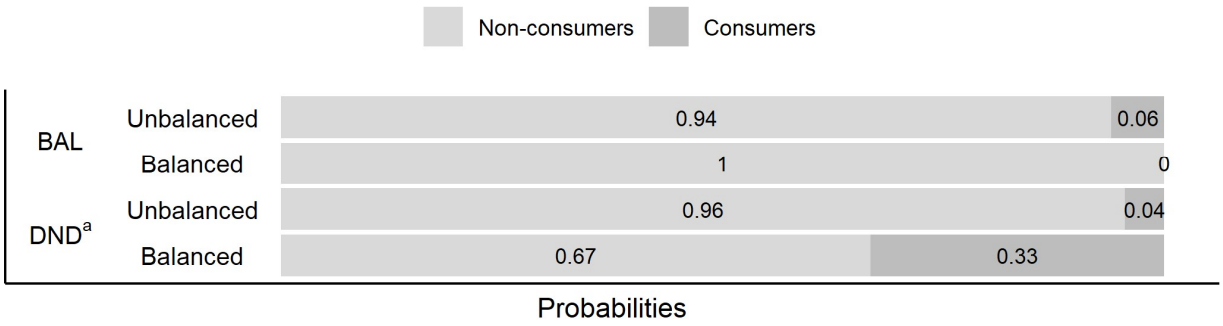

Figure 7. Probabilities of Consumption of Consumed versus Non-consumed Food Categories by Dietary Pattern

[a] Significant odds ratio for Unbalanced vs. Balanced comparing consumers to non-consumers ($p<0.05$)

CHAPTER V: EPILOGUE

Summary of Findings and Implications

Data from the RIGHT Track Parent and RIGHT Track Health longitudinal studies were used to address the following study aims: i) characterize unique trajectories of BMI from childhood through adolescence (4 to 18 year) and describe the association between BMI trajectory membership and body composition and biomarkers in emerging adulthood including percent body fat, fasting glucose, fasting insulin, and HOMA-IR; ii) determine the prospective association between pre-school self-regulation and BMI trajectory membership; and iii) describe unique patterns of adolescent dietary consumption and determine the corresponding association between adolescent dietary pattern membership and future anthropometrics and biomarkers including BMI, percent body fat, fasting glucose, fasting insulin, and HOMA-IR collected in emerging adulthood. Participants in the RIGHT Track studies were characterized by two unique longitudinal BMI trajectories: i) stable normal weight and ii) normal weight to overweight transition. Compared to the stable normal weight group, membership in the normal weight to overweight transition group was positively associated with fasting glucose, fasting insulin, HOMA-IR, waist circumference, and percent body fat, even after controlling for sex, race, and socioeconomic status. Results were attenuated when each model additionally controlled for adult waist circumference or adult percent body fat. Importantly, higher childhood self-regulatory behavior, as measured by a gift-delay task, decreased the likelihood of a child being in the "normal weight to overweight transition" group, which was shown to be associated with higher levels of biomarkers that could lead to future metabolic dysfunction. Higher childhood self-regulation as measured by a food-related task was not associated with BMI trajectory membership. However, moderate food-related self-regulation was suggestive of decreased risk of membership in the BMI transition group compared to those who were considered unregulated ($p=0.09$). Even though this relation was not statistically significant, this finding supports exploration of moderation as a useful technique when educating children on dietary intake.

In the current study, two unique patterns of adolescent dietary intake were found in our sample: i) balanced (higher consumption of unsweetened beverages, fruits, and non-starchy vegetables) and ii) unbalanced (greater consumption of sugar-sweetened beverages, fried potatoes, and full fat/fried meats). While there were differences in types of foods consumed by those in each of these patterns, diet quality was poor in both patterns as shown by low Healthy Eating Index scores. No significant associations were found between adolescent dietary patterns and any of the adult health measures (i.e., fasting glucose, fasting insulin, HOMA-IR, percent body fat or BMI).

This study provides insight into longitudinal BMI patterns for children and adolescents and corresponding childhood behavioral predictors that could serve as targets for public health interventions to decrease obesity-related health risks. Additional research is needed to examine self-regulatory behaviors at different time points during childhood to determine the best age at which implementation of behavioral interventions would be most effective in minimizing future adiposity-related health risks. More specifically, the two measures of self-regulation used in this study had little variability at age 4. Researching these measures throughout childhood may allow for capturing data at times when self-regulatory behaviors are more diverse and thereby provide additional insight into the relation between self-regulation and BMI patterns.

Research that further explores dietary patterns in the RIGHT Track sample would be of interest, particularly how dietary patterns in adolescence compare to patterns in emerging adulthood. We did see that, on average, those individuals who had dietary data during both adolescence and emerging adulthood did experience changes in the amounts of some foods they consumed (i.e., high consumer during adolescence versus low consumer during adulthood, etc.). Further analyses could explore if similar dietary patterns exist during emerging adulthood and determine if there are any differences in health markers based on longitudinal dietary patterns. For example, do biomarker values differ when comparing individuals who maintain their adolescent dietary pattern to those who transition into a different pattern as they mature? Additionally, while it is not in my wheelhouse to pursue, creation of insulin cut points for non-adult populations would be an important step in early identification of metabolic dysfunction. Similarly, development of insulin monitoring tools, like those available for glucose, has the potential to prevent the transition to diabetes for so many individuals.

Experiences and Challenges

My time at UNC-G has been incredible. I am so thankful to have had the opportunity to work with so many amazing researchers, who are perhaps even more importantly also incredible humans! In addition to having encouraging faculty and classmates, I am extremely grateful to RIGHT Track researchers for being so open to letting me move forward on my dissertation research. It is a heart-warming feeling to be welcomed onto a project that took a multitude of researchers multiple decades to plan, implement, and collect data! I am so glad to have been able to expand my knowledge of statistical methods related to longitudinal anthropometrics and dietary intake; and additionally, to have benefitted from the multidisciplinary aspect of the RIGHT Track research which allowed me to learn about self-regulation, a topic with corresponding assessment techniques that were totally unfamiliar to me.

The biggest lesson I learned during this experience was: PANDEMICS ARE HARD. They are hard in oh so many ways. I have always known that I do my best work as part of a team where I am able to contribute my strengths and benefit from collaboration with colleagues that helps me improve on my weaknesses. While I am incredibly grateful to have been 'virtually' surrounded by incredibly supportive faculty, friends, and family, a year of almost complete isolation certainly took its toll on both my mental and physical health. My feelings can most efficiently be expressed by the following memes:

Yay!

I'm getting a PhD!

I. Can't. Go. On.

Did I do it? Is it over?

Oh…why hello there, pandemic.

REFERENCES

Abreu, A. P., & Kaiser, U. B. (2016). Pubertal development and regulation. *Lancet Diabetes Endocrinol, 4*(3), 254-264. doi:10.1016/S2213-8587(15)00418-0

Achenbach, T. M. (1992). Manual for the child behavior checklist/2-3 and 1992 profile. In *Burlington, VT; University of VT Department of Psychiatry.*

Adeva-Andany, M. M., Martinez-Rodriguez, J., Gonzalez-Lucan, M., Fernandez-Fernandez, C., & Castro-Quintela, E. (2019). Insulin resistance is a cardiovascular risk factor in humans. *Diabetes Metab Syndr, 13*(2), 1449-1455. doi:10.1016/j.dsx.2019.02.023

Agirbasli, M., Tanrikulu, A. M., & Berenson, G. S. (2016). Metabolic Syndrome: Bridging the Gap from Childhood to Adulthood. *Cardiovasc Ther, 34*(1), 30-36. doi:10.1111/1755-5922.12165

Allom, V., & Mullan, B. (2015). Two inhibitory control training interventions designed to improve eating behaviour and determine mechanisms of change. *Appetite, 89*, 282-290. doi:10.1016/j.appet.2015.02.022

Ambrosini, G. L., Huang, R. C., Mori, T. A., Hands, B. P., O'Sullivan, T. A., de Klerk, N. H., . . . Oddy, W. H. (2010). Dietary patterns and markers for the metabolic syndrome in Australian adolescents. *Nutr Metab Cardiovasc Dis, 20*(4), 274-283. doi:10.1016/j.numecd.2009.03.024

Andruff, H., Carraro, N., Thompson, A., & Gaudreau, P. (2009). Latent Class Growth Modelling: A Tutorial. *Tutor Quant Methods Psychol, 5*(1), 11-24.

Anzman-Frasca, S., Francis, L. A., & Birch, L. L. (2015). Inhibitory Control is Associated with Psychosocial, Cognitive, and Weight Outcomes in a Longitudinal Sample of Girls. *Transl Issues Psychol Sci, 1*(3), 203-216. doi:10.1037/tps0000028

Arnett, J. J. (2000). Emerging adulthood. A theory of development from the late teens through the twenties. *Am Psychol, 55*(5), 469-480.

Augustus-Horvath, C. L., & Tylka, T. L. (2011). The acceptance model of intuitive eating: a comparison of women in emerging adulthood, early adulthood, and middle adulthood. *J Couns Psychol, 58*(1), 110-125. doi:10.1037/a0022129

Bahreini Esfahani, N., Ganjali Dashti, N., Ganjali Dashti, M., Noorv, M. I., Koon, P. B., Talib, R. A., & Lubis, S. H. (2016). Dietary Predictors of Overweight and Obesity in Iranian Adolescents. *Iran Red Crescent Med J, 18*(9), e25569. doi:10.5812/ircmj.25569

Bahreynian, M., Paknahad, Z., & Maracy, M. R. (2013). Major dietary patterns and their associations with overweight and obesity among Iranian children. *Int J Prev Med, 4*(4), 448-458. Retrieved from https://www.ncbi.nlm.nih.gov/pubmed/23671778

Balantekin, K. N., Birch, L. L., & Savage, J. S. (2015). Patterns of weight-control behavior among 15 year old girls. *Int J Eat Disord, 48*(6), 589-600. doi:10.1002/eat.22426

Batterink, L., Yokum, S., & Stice, E. (2010). Body mass correlates inversely with inhibitory control in response to food among adolescent girls: an fMRI study. *Neuroimage, 52*(4), 1696-1703. doi:10.1016/j.neuroimage.2010.05.059

Berge, J. M., & Everts, J. C. (2011). Family-Based Interventions Targeting Childhood Obesity: A Meta-Analysis. *Child Obes, 7*(2), 110-121. doi:10.1089/chi.2011.07.02.1004.berge

Bergmeier, H., Skouteris, H., Horwood, S., Hooley, M., & Richardson, B. (2014). Associations between child temperament, maternal feeding practices and child body mass index during the preschool years: a systematic review of the literature. *Obes Rev, 15*(1), 9-18. doi:10.1111/obr.12066

Bertin, M., Touvier, M., Dubuisson, C., Dufour, A., Havard, S., Lafay, L., . . . Lioret, S. (2016). Dietary patterns of French adults: associations with demographic, socio-economic and behavioural factors. *J Hum Nutr Diet, 29*(2), 241-254. doi:10.1111/jhn.12315

Berz, J. P., Singer, M. R., Guo, X., Daniels, S. R., & Moore, L. L. (2011). Use of a DASH food group score to predict excess weight gain in adolescent girls in the National Growth and Health Study. *Arch Pediatr Adolesc Med, 165*(6), 540-546.

Biesanz, J. C., Deeb-Sossa, N., Papadakis, A. A., Bollen, K. A., & Curran, P. J. (2004). The role of coding time in estimating and interpreting growth curve models. *Psychol Methods, 9*(1), 30-52. doi:10.1037/1082-989X.9.1.30

Blandon, A. Y., Calkins, S. D., Keane, S. P., & O'Brien, M. (2010). Contributions of child's physiology and maternal behavior to children's trajectories of temperamental reactivity. *Dev Psychol, 46*(5), 1089-1102. doi:10.1037/a0020678

Borland, S. E., Robinson, S. M., Crozier, S. R., Inskip, H. M., & Group, S. W. S. S. (2008). Stability of dietary patterns in young women over a 2-year period. *Eur J Clin Nutr, 62*(1), 119-126. doi:10.1038/sj.ejcn.1602684

Bouchard, C. (2007). BMI, fat mass, abdominal adiposity and visceral fat: where is the 'beef'? *Int J Obes (Lond), 31*(10), 1552-1553. doi:10.1038/sj.ijo.0803653

Bowman, S., Clemens, J., Shimizu, M., Friday, J., & Moshfegh, A. (2018). Food Patterns Equivalents Database 2015-2016: Methodology and User Guide [Online]. Retrieved from Available at: http://www.ars.usda.gov/nea/bhnrc/fsrg from Food Surveys Research Group, Beltsville Human Nutrition Research Center, Agricultural Research Service, U.S. Department of Agriculture Available at: http://www.ars.usda.gov/nea/bhnrc/fsrg

Buscot, M. J., Thomson, R. J., Juonala, M., Sabin, M. A., Burgner, D. P., Lehtimaki, T., . . . Magnussen, C. G. (2018). Distinct child-to-adult body mass index trajectories are associated with different levels of adult cardiometabolic risk. *Eur Heart J, 39*(24), 2263-2270. doi:10.1093/eurheartj/ehy161

Calkins, S. D., Dedmon, S. E., Gill, K. L., Lomax, L. E., & Johnson, L. M. (2002). Frustration in infancy: Implications for emotion regulation, physiological processes, and temperament. *Infancy, 3*, 175-197.

Calkins, S. D., & Keane, S. P. (2009). Developmental origins of early antisocial behavior. *Dev Psychopathol, 21*(4), 1095-1109. doi:10.1017/S095457940999006X

CDC. Defining Adult Overweight and Obesity. Retrieved from https://www.cdc.gov/obesity/adult/defining.html

CDC. Defining Childhood Obesity. Retrieved from https://www.cdc.gov/obesity/childhood/defining.html

CDC. A SAS Program for the 2000 CDC Growth Charts (ages 0 to <20 years). Retrieved from https://www.cdc.gov/nccdphp/dnpao/growthcharts/resources/sas.htm

Celeux, G., & Soromenho, G. (1996). An entropy criterion for assessing the number of clusters in a mixture model. *J Classif, 13*, 195-212.

Cespedes, E. M., & Hu, F. B. (2015). Dietary patterns: from nutritional epidemiologic analysis to national guidelines. *Am J Clin Nutr, 101*(5), 899-900. doi:10.3945/ajcn.115.110213

Choong, M. K., & Tsafnat, G. (2012). The implications of biomarker evidence for systematic reviews. *BMC Med Res Methodol, 12*, 176. doi:10.1186/1471-2288-12-176

Clarke, P. J., O'Malley, P. M., Schulenberg, J. E., & Johnston, L. D. (2010). Midlife health and socioeconomic consequences of persistent overweight across early adulthood: findings from a national survey of American adults (1986-2008). *Am J Epidemiol, 172*(5), 540-548. doi:10.1093/aje/kwq156

Cole, T. J., Faith, M. S., Pietrobelli, A., & Heo, M. (2005). What is the best measure of adiposity change in growing children: BMI, BMI %, BMI z-score or BMI centile? *Eur J Clin Nutr, 59*(3), 419-425. doi:10.1038/sj.ejcn.1602090

Costacou, T., Crandell, J., Kahkoska, A. R., Liese, A. D., Dabelea, D., Lawrence, J. M., . . . Mottl, A. K. (2018). Dietary Patterns Over Time and Microalbuminuria in Youth and Young Adults with Type 1 Diabetes: The SEARCH Nutrition Ancillary Study. *Diabetes Care, 41*(8), 1615-1622. doi:10.2337/dc18-0319

Cunha, C. M., Costa, P. R. F., de Oliveira, L. P. M., Queiroz, V. A. O., Pitangueira, J. C. D., & Oliveira, A. M. (2018). Dietary patterns and cardiometabolic risk factors among adolescents: systematic review and meta-analysis. *Br J Nutr, 119*(8), 859-879. doi:10.1017/S0007114518000533

Curran, P. J., Obeidat, K., & Losardo, D. (2010). Twelve Frequently Asked Questions About Growth Curve Modeling. *J Cogn Dev, 11*(2), 121-136. doi:10.1080/15248371003699969

da Costa, K. G., Price, M., Bortolotti, H., de Medeiros Rego, M. L., Cabral, D. A. R., Langer, R. D., . . . Fontes, E. B. (2019). Fat mass predicts food-specific inhibitory control in children. *Physiol Behav, 204*, 155-161. doi:10.1016/j.physbeh.2019.02.031

Demerath, E. W., Schubert, C. M., Maynard, L. M., Sun, S. S., Chumlea, W. C., Pickoff, A., . . . Siervogel, R. M. (2006). Do changes in body mass index percentile reflect changes in body composition in children? Data from the Fels Longitudinal Study. *Pediatrics, 117*(3), e487-495. doi:10.1542/peds.2005-0572

Dietz, W. H., & Bellizzi, M. C. (1999). Introduction: the use of body mass index to assess obesity in children. *Am J Clin Nutr, 70*(1), 123S-125S. doi:10.1093/ajcn/70.1.123s

Eisenberg, N. (2012). Temperamental Effortful Control (Self-Regulation). In *Encyclopedia on Early Childhood Development*. Retrieved from http://www.child-encyclopedia.com/sites/default/files/textes-experts/en/892/temperamental-effortful-control-self-regulation.pdf

Eriksson, J. G., Kajantie, E., Lampl, M., & Osmond, C. (2015). Trajectories of body mass index amongst children who develop type 2 diabetes as adults. *J Intern Med, 278*(2), 219-226. doi:10.1111/joim.12354

Fruh, S. M. (2017). Obesity: Risk factors, complications, and strategies for sustainable long-term weight management. *J Am Assoc Nurse Pract, 29*(S1), S3-S14. doi:10.1002/2327-6924.12510

Gagne, J. R., Van Hulle, C. A., Aksan, N., Essex, M. J., & Goldsmith, H. H. (2011). Deriving childhood temperament measures from emotion-eliciting behavioral episodes: scale construction and initial validation. *Psychol Assess, 23*(2), 337-353. doi:10.1037/a0021746

Garden, F. L., Marks, G. B., Simpson, J. M., & Webb, K. L. (2012). Body mass index (BMI) trajectories from birth to 11.5 years: relation to early life food intake. *Nutrients, 4*(10), 1382-1398. doi:10.3390/nu4101382

Gedela, S., Appa Rao, A., & Medicherla, N. R. (2007). Identification of biomarkers for type 2 diabetes and its complications: a bioinformatic approach. *Int J Biomed Sci, 3*(4), 229-236. Retrieved from https://www.ncbi.nlm.nih.gov/pubmed/23675048

Geserick, M., Vogel, M., Gausche, R., Lipek, T., Spielau, U., Keller, E., . . . Korner, A. (2018). Acceleration of BMI in Early Childhood and Risk of Sustained Obesity. *N Engl J Med, 379*(14), 1303-1312. doi:10.1056/NEJMoa1803527

Giannini, C., Weiss, R., Cali, A., Bonadonna, R., Santoro, N., Pierpont, B., . . . Caprio, S. (2012). Evidence for early defects in insulin sensitivity and secretion before the onset of glucose dysregulation in obese youths: a longitudinal study. *Diabetes, 61*(3), 606-614. doi:10.2337/db11-1111

Gilmore, K. (2019). Is Emerging Adulthood a New Developmental Phase? *J Am Psychoanal Assoc, 67*(4), 625-653. doi:10.1177/0003065119868680

Ginsberg, H. N. (2000). Insulin resistance and cardiovascular disease. *J Clin Invest, 106*(4), 453-458. doi:10.1172/JCI10762

Goldsmith, H. H. Preschool Version of Lab-TAB. Retrieved from https://goldsmithtwins.waisman.wisc.edu/instruments/#preschool-version-of-lab-tab

Goldsmith, H. H., Reilly, J., Lemery, K. S., Longley, S., & Prescott, A. (1995). *Preschool laboratory temperament assessment battery (version 0.5)*. Retrieved from Department of Psychology.:

Graziano, P. A., Calkins, S. D., & Keane, S. P. (2010). Toddler self-regulation skills predict risk for pediatric obesity. *Int J Obes (Lond), 34*(4), 633-641. doi:10.1038/ijo.2009.288

Graziano, P. A., Kelleher, R., Calkins, S. D., Keane, S. P., & Brien, M. O. (2013). Predicting weight outcomes in preadolescence: the role of toddlers' self-regulation skills and the temperament dimension of pleasure. *Int J Obes (Lond), 37*(7), 937-942. doi:10.1038/ijo.2012.165

Gutierrez-Pliego, L. E., Camarillo-Romero Edel, S., Montenegro-Morales, L. P., & Garduno-Garcia Jde, J. (2016). Dietary patterns associated with body mass index (BMI) and lifestyle in Mexican adolescents. *BMC Public Health, 16*(1), 850. doi:10.1186/s12889-016-3527-6

Hales, C. M., Carroll, M. D., Fryar, C. D., & Ogden, C. L. (2017). *Prevalence of Obesity Among Adults and Youth: United States, 2015-2016*. Retrieved from

Hamaker, E. L., & Grasman, R. P. (2014). To center or not to center? Investigating inertia with a multilevel autoregressive model. *Front Psychol, 5*, 1492. doi:10.3389/fpsyg.2014.01492

Hoare, E., Dash, S. R., Jennings, G. L., & Kingwell, B. A. (2018). Sex-Specific Associations in Nutrition and Activity-Related Risk Factors for Chronic Disease: Australian Evidence from Childhood to Emerging Adulthood. *Int J Environ Res Public Health, 15*(2). doi:10.3390/ijerph15020214

Hojhabrimanesh, A., Akhlaghi, M., Rahmani, E., Amanat, S., Atefi, M., Najafi, M., . . . Faghih, S. (2017). A Western dietary pattern is associated with higher blood pressure in Iranian adolescents. *Eur J Nutr, 56*(1), 399-408. doi:10.1007/s00394-015-1090-z

Hollingshead, A. D. B. (1975). *Four factor index of social status.* New Haven, CT: Yale University Press.

Hu, F. B. (2002). Dietary pattern analysis: a new direction in nutritional epidemiology. *Curr Opin Lipidol, 13*(1), 3-9. doi:10.1097/00041433-200202000-00002
Hu, J., Leite, W. L., & Gao, M. (2017). An evaluation of the use of covariates to assist in class enumeration in linear growth mixture modeling. *Behav Res Methods, 49*(3), 1179-1190. doi:10.3758/s13428-016-0778-1
Huang, D. Y., Lanza, H. I., Wright-Volel, K., & Anglin, M. D. (2013). Developmental trajectories of childhood obesity and risk behaviors in adolescence. *J Adolesc, 36*(1), 139-148. doi:10.1016/j.adolescence.2012.10.005
Iannotti, R. J., & Wang, J. (2013a). Patterns of physical activity, sedentary behavior, and diet in U.S. adolescents. *J Adolesc Health, 53*(2), 280-286. doi:10.1016/j.jadohealth.2013.03.007
Iannotti, R. J., & Wang, J. (2013b). Trends in physical activity, sedentary behavior, diet, and BMI among US adolescents, 2001-2009. *Pediatrics, 132*(4), 606-614. doi:10.1542/peds.2013-1488
Isong, I. A., Richmond, T., Avendano, M., & Kawachi, I. (2018). Racial/Ethnic Disparities: a Longitudinal Study of Growth Trajectories Among US Kindergarten Children. *J Racial Ethn Health Disparities, 5*(4), 875-884. doi:10.1007/s40615-017-0434-1
Jansen, P. W., Mensah, F. K., Nicholson, J. M., & Wake, M. (2013). Family and neighbourhood socioeconomic inequalities in childhood trajectories of BMI and overweight: longitudinal study of Australian children. *PLoS One, 8*(7), e69676. doi:10.1371/journal.pone.0069676
Johnson, J. L., Duick, D. S., Chui, M. A., & Aldasouqi, S. A. (2010). Identifying prediabetes using fasting insulin levels. *Endocr Pract, 16*(1), 47-52. doi:10.4158/EP09031.OR
Jun, H. J., Corliss, H. L., Nichols, L. P., Pazaris, M. J., Spiegelman, D., & Austin, S. B. (2012). Adult body mass index trajectories and sexual orientation: the Nurses' Health Study II. *Am J Prev Med, 42*(4), 348-354. doi:10.1016/j.amepre.2011.11.011
Jung, J., & Wickrama, K. A. S. (2008). An Introduction to Latent Class Growth Analysis and Growth Mixture Modeling. *Soc Personal Psychol Compass, 2*(1), 302-217.
Kelsey, M. M., Zaepfel, A., Bjornstad, P., & Nadeau, K. J. (2014). Age-related consequences of childhood obesity. *Gerontology, 60*(3), 222-228. doi:10.1159/000356023
Knopp, J. L., Holder-Pearson, L., & Chase, J. G. (2019). Insulin Units and Conversion Factors: A Story of Truth, Boots, and Faster Half-Truths. *J Diabetes Sci Technol, 13*(3), 597-600. doi:10.1177/1932296818805074
Kochanska, G., Murray, K., Jacques, T. Y., Koenig, A. L., & Vandegeest, K. A. (1996). Inhibitory control in young children and its role in emerging internalization. *Child Dev, 67*(2), 490-507.
Krebs-Smith, S. M., Pannucci, T. E., Subar, A. F., Kirkpatrick, S. I., Lerman, J. L., Tooze, J. A., . . . Reedy, J. (2018). Update of the Healthy Eating Index: HEI-2015. *J Acad Nutr Diet, 118*(9), 1591-1602. doi:10.1016/j.jand.2018.05.021
Kropski, J. A., Keckley, P. H., & Jensen, G. L. (2008). School-based obesity prevention programs: an evidence-based review. *Obesity (Silver Spring), 16*(5), 1009-1018. doi:10.1038/oby.2008.29
Kubzansky, L. D., Gilthorpe, M. S., & Goodman, E. (2012). A prospective study of psychological distress and weight status in adolescents/young adults. *Ann Behav Med, 43*(2), 219-228. doi:10.1007/s12160-011-9323-8
Kwon, S., Janz, K. F., Letuchy, E. M., Burns, T. L., & Levy, S. M. (2017). Association between body mass index percentile trajectories in infancy and adiposity in childhood and early adulthood. *Obesity (Silver Spring), 25*(1), 166-171. doi:10.1002/oby.21673

Lane, S. P., Bluestone, C., & Burke, C. T. (2013). Trajectories of BMI from early childhood through early adolescence: SES and psychosocial predictors. *Br J Health Psychol, 18*(1), 66-82. doi:10.1111/j.2044-8287.2012.02078.x

Lanigan, J., Tee, L., & Brandreth, R. (2019). Childhood obesity. *Medicine, 47*(3), 190-194. doi:10.1016/j.mpmed.2018.12.007

Lanza, S. T., & Rhoades, B. L. (2013). Latent class analysis: an alternative perspective on subgroup analysis in prevention and treatment. *Prev Sci, 14*(2), 157-168. doi:10.1007/s11121-011-0201-1

LeCroy, M. N., Truesdale, K. P., Matheson, D. M., Karp, S. M., Moore, S. M., Robinson, T. N., . . . Thomas, A. J. (2019). Snacking characteristics and patterns and their associations with diet quality and BMI in the Childhood Obesity Prevention and Treatment Research Consortium. *Public Health Nutr*, 1-11. doi:10.1017/S1368980019000958

Lee, S., Bacha, F., Gungor, N., & Arslanian, S. A. (2006). Waist circumference is an independent predictor of insulin resistance in black and white youths. *J Pediatr, 148*(2), 188-194. doi:10.1016/j.jpeds.2005.10.001

Levy, J., Atkinson, A. B., Bell, P. M., McCance, D. R., & Hadden, D. R. (1998). Beta-cell deterioration determines the onset and rate of progression of secondary dietary failure in type 2 diabetes mellitus: the 10-year follow-up of the Belfast Diet Study. *Diabet Med, 15*(4), 290-296.

Li, C., Goran, M. I., Kaur, H., Nollen, N., & Ahluwalia, J. S. (2007). Developmental trajectories of overweight during childhood: role of early life factors. *Obesity (Silver Spring), 15*(3), 760-771. doi:10.1038/oby.2007.585

Lipsky, L. M., Nansel, T. R., Haynie, D. L., Liu, D., Li, K., Pratt, C. A., . . . Simons-Morton, B. (2017). Diet quality of US adolescents during the transition to adulthood: changes and predictors. *Am J Clin Nutr, 105*(6), 1424-1432. doi:10.3945/ajcn.116.150029

Liu, J. X., Liu, J. H., Frongillo, E. A., Boghossian, N. S., Cai, B., & Hazlett, L. J. (2017). Body mass index trajectories during infancy and pediatric obesity at 6 years. *Ann Epidemiol, 27*(11), 708-715 e701. doi:10.1016/j.annepidem.2017.10.008

Looman, M., Boshuizen, H. C., Feskens, E. J., & Geelen, A. (2019). Using enhanced regression calibration to combine dietary intake estimates from 24 h recall and FFQ reduces bias in diet-disease associations. *Public Health Nutr*, 1-9. doi:10.1017/S1368980019001563

Lopez-Jaramillo, P., Velandia-Carrillo, C., Gomez-Arbelaez, D., & Aldana-Campos, M. (2014). Is the present cut-point to define type 2 diabetes appropriate in Latin-Americans? *World J Diabetes, 5*(6), 747-755. doi:10.4239/wjd.v5.i6.747

Ma, Y., Olendzki, B. C., Pagoto, S. L., Hurley, T. G., Magner, R. P., Ockene, I. S., . . . Hebert, J. R. (2009). Number of 24-hour diet recalls needed to estimate energy intake. *Ann Epidemiol, 19*(8), 553-559. doi:10.1016/j.annepidem.2009.04.010

Magee, C. A., Caputi, P., & Iverson, D. C. (2013). Identification of distinct body mass index trajectories in Australian children. *Pediatr Obes, 8*(3), 189-198. doi:10.1111/j.2047-6310.2012.00112.x

Maia, E. G., Silva, L., Santos, M. A. S., Barufaldi, L. A., Silva, S. U. D., & Claro, R. M. (2018). Dietary patterns, sociodemographic and behavioral characteristics among Brazilian adolescents. *Rev Bras Epidemiol, 21*(suppl 1), e180009. doi:10.1590/1980-549720180009.supl.1

Martin, C. L., Siega-Riz, A. M., Sotres-Alvarez, D., Robinson, W. R., Daniels, J. L., Perrin, E. M., & Stuebe, A. M. (2016). Maternal Dietary Patterns are Associated with Lower Levels

of Cardiometabolic Markers during Pregnancy. *Paediatr Perinat Epidemiol, 30*(3), 246-255. doi:10.1111/ppe.12279
Masyn, K. (2013). Latent Class Analysis and Finite Mixture Modeling. In T. Little (Ed.), *The Oxford Handbook of Quantitative Methods* (Vol. 2, pp. 551-611).
Mattsson, M., Maher, G. M., Boland, F., Fitzgerald, A. P., Murray, D. M., & Biesma, R. (2019). Group-based trajectory modelling for BMI trajectories in childhood: A systematic review. *Obes Rev, 20*(7), 998-1015. doi:10.1111/obr.12842
Moreno-Black, G., Boles, S., Johnson-Shelton, D., & Evers, C. (2016). Exploring Categorical Body Mass Index Trajectories in Elementary School Children. *J Sch Health, 86*(7), 495-506. doi:10.1111/josh.12402
Moreno, L. A., Rodriguez, G., Fleta, J., Bueno-Lozano, M., Lazaro, A., & Bueno, G. (2010). Trends of dietary habits in adolescents. *Crit Rev Food Sci Nutr, 50*(2), 106-112. doi:10.1080/10408390903467480
Munthali, R. J., Kagura, J., Lombard, Z., & Norris, S. A. (2016). Childhood adiposity trajectories are associated with late adolescent blood pressure: birth to twenty cohort. *BMC Public Health, 16*, 665. doi:10.1186/s12889-016-3337-x
Muthen, B. (2004). Latent Variable Analysis: Growth Mixture Modeling and Related Techniques for Longitudinal Data. In D. Kaplan (Ed.), *The SAGE Handbook of Quantitative Methodology for the Social Sciences* (pp. 345-368): Thousand Oaks: Sage Publications.
Muthén, B. (2006). The potential of growth mixture modelling. *Infant Child Dev, 15*(6), 623-625. doi:10.1002/icd.482
Muthen, B., & Asparouhov, T. (2015). Growth mixture modeling with non-normal distributions. *Stat Med, 34*(6), 1041-1058. doi:10.1002/sim.6388
Muthen, B. O., & Khoo, S.-T. (1998). Longitudinal Studies of Achievement Growth using Latent Variable Modeling. *Learn Individ Differ 10*(2), 73-101.
Muthén, L. K., & Muthén, B. O. (2010). Growth Modeling With Latent Variables Using Mplus: Introductory And Intermediate Growth Models. In. www.statmodel.com.
NCI. Visualization and Interpretation of HEI Scores. Retrieved from https://epi.grants.cancer.gov/hei/interpret-visualize-hei-scores.html
Nedelec, R., Miettunen, J., Mannikko, M., Jarvelin, M. R., & Sebert, S. (2020). Maternal and infant prediction of the child BMI trajectories; studies across two generations of Northern Finland birth cohorts. *Int J Obes (Lond)*. doi:10.1038/s41366-020-00695-0
Nelson, M. C., Story, M., Larson, N. I., Neumark-Sztainer, D., & Lytle, L. A. (2008). Emerging adulthood and college-aged youth: an overlooked age for weight-related behavior change. *Obesity (Silver Spring), 16*(10), 2205-2211. doi:10.1038/oby.2008.365
Nonnemaker, J. M., Morgan-Lopez, A. A., Pais, J. M., & Finkelstein, E. A. (2009). Youth BMI trajectories: evidence from the NLSY97. *Obesity (Silver Spring), 17*(6), 1274-1280. doi:10.1038/oby.2009.5
Nylund, K., Asparouhov, T., & Muthen, B. (2007). Deciding on the Number of Classes in Latent Class Analysis and Growth Mixture Modeling: A Monte Carlo Simulation Study. *Structural Equation Modeling, 14*(4), 535-569.
O'Neil, A., Quirk, S. E., Housden, S., Brennan, S. L., Williams, L. J., Pasco, J. A., . . . Jacka, F. N. (2014). Relationship between diet and mental health in children and adolescents: a systematic review. *Am J Public Health, 104*(10), e31-42. doi:10.2105/AJPH.2014.302110
Oluwagbemigun, K., Buyken, A. E., Alexy, U., Schmid, M., Herder, C., & Nothlings, U. (2019). Developmental trajectories of body mass index from childhood into late adolescence and

subsequent late adolescence-young adulthood cardiometabolic risk markers. *Cardiovasc Diabetol, 18*(1), 9. doi:10.1186/s12933-019-0813-5

Ostbye, T., Malhotra, R., & Landerman, L. R. (2011). Body mass trajectories through adulthood: results from the National Longitudinal Survey of Youth 1979 Cohort (1981-2006). *Int J Epidemiol, 40*(1), 240-250. doi:10.1093/ije/dyq142

Pauli-Pott, U., Albayrak, O., Hebebrand, J., & Pott, W. (2010). Association between inhibitory control capacity and body weight in overweight and obese children and adolescents: dependence on age and inhibitory control component. *Child Neuropsychol, 16*(6), 592-603. doi:10.1080/09297049.2010.485980

Paynter, L., Koehler, E., Howard, A. G., Herring, A. H., & Gordon-Larsen, P. (2015). Characterizing long-term patterns of weight change in China using latent class trajectory modeling. *PLoS One, 10*(2), e0116190. doi:10.1371/journal.pone.0116190

Peneau, S., Giudici, K. V., Gusto, G., Goxe, D., Lantieri, O., Hercberg, S., & Rolland-Cachera, M. F. (2017). Growth Trajectories of Body Mass Index during Childhood: Associated Factors and Health Outcome at Adulthood. *J Pediatr, 186*, 64-71 e61. doi:10.1016/j.jpeds.2017.02.010

Power, T. G., Olivera, Y. A., Hill, R. A., Beck, A. D., Hopwood, V., Garcia, K. S., . . . Hughes, S. O. (2016). Emotion regulation strategies and childhood obesity in high risk preschoolers. *Appetite, 107*, 623-627. doi:10.1016/j.appet.2016.09.008

Prinz, N., Schwandt, A., Becker, M., Denzer, C., Flury, M., Fritsch, M., . . . Holl, R. W. (2018). Trajectories of Body Mass Index from Childhood to Young Adulthood among Patients with Type 1 Diabetes-A Longitudinal Group-Based Modeling Approach Based on the DPV Registry. *J Pediatr*. doi:10.1016/j.jpeds.2018.05.014

Pryor, L. E., Tremblay, R. E., Boivin, M., Touchette, E., Dubois, L., Genolini, C., . . . Cote, S. M. (2011). Developmental trajectories of body mass index in early childhood and their risk factors: an 8-year longitudinal study. *Arch Pediatr Adolesc Med, 165*(10), 906-912. doi:10.1001/archpediatrics.2011.153

Raftery, A. E. (1995). Bayseian Model Selection in Social Research. *Sociol Methodol, 25*, 111-163.

Ram, N., & Grimm, K. J. (2009). Growth Mixture Modeling: A Method for Identifying Differences in Longitudinal Change Among Unobserved Groups. *Int J Behav Dev, 33*(6), 565-576. doi:10.1177/0165025409343765

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models: applications and data analysis methods* (2nd ed.). Thousand Oaks: Sage Publications.

Rivas-Crespo, M. F. (2015). Comment on Boyko and Jensen. Do We Know What Homeostatis Model Assessment Measures? If Not, Does It Matter? Diabetes Care 2007;30:2725-2728. *Diabetes Care, 38*(12), e213. doi:10.2337/dc15-1172

Rocha, N. P., Milagres, L. C., Longo, G. Z., Ribeiro, A. Q., & Novaes, J. F. (2017). Association between dietary pattern and cardiometabolic risk in children and adolescents: a systematic review. *J Pediatr (Rio J), 93*(3), 214-222. doi:10.1016/j.jped.2017.01.002

Ruiz, L. D., Zuelch, M. L., Dimitratos, S. M., & Scherr, R. E. (2019). Adolescent Obesity: Diet Quality, Psychosocial Health, and Cardiometabolic Risk Factors. *Nutrients, 12*(1). doi:10.3390/nu12010043

Rzehak, P., Oddy, W. H., Mearin, M. L., Grote, V., Mori, T. A., Szajewska, H., . . . Project, W. P. w. g. o. t. E. N. (2017). Infant feeding and growth trajectory patterns in childhood and

body composition in young adulthood. *Am J Clin Nutr, 106*(2), 568-580. doi:10.3945/ajcn.116.140962
Saydah, S., Bullard, K. M., Cheng, Y., Ali, M. K., Gregg, E. W., Geiss, L., & Imperatore, G. (2014). Trends in cardiovascular disease risk factors by obesity level in adults in the United States, NHANES 1999-2010. *Obesity (Silver Spring), 22*(8), 1888-1895. doi:10.1002/oby.20761
Schlam, T. R., Wilson, N. L., Shoda, Y., Mischel, W., & Ayduk, O. (2013). Preschoolers' delay of gratification predicts their body mass 30 years later. *J Pediatr, 162*(1), 90-93. doi:10.1016/j.jpeds.2012.06.049
Schwingshackl, L., Bogensberger, B., & Hoffmann, G. (2018). Diet Quality as Assessed by the Healthy Eating Index, Alternate Healthy Eating Index, Dietary Approaches to Stop Hypertension Score, and Health Outcomes: An Updated Systematic Review and Meta-Analysis of Cohort Studies. *J Acad Nutr Diet, 118*(1), 74-100 e111. doi:10.1016/j.jand.2017.08.024
Shrestha, R., & Copenhaver, M. (2015). Long-Term Effects of Childhood Risk Factors on Cardiovascular Health During Adulthood. *Clin Med Rev Vasc Health, 7*, 1-5. doi:10.4137/CMRVH.S29964
Simmonds, M., Llewellyn, A., Owen, C. G., & Woolacott, N. (2016). Predicting adult obesity from childhood obesity: a systematic review and meta-analysis. *Obes Rev, 17*(2), 95-107. doi:10.1111/obr.12334
Singh, B., & Saxena, A. (2010). Surrogate markers of insulin resistance: A review. *World J Diabetes, 1*(2), 36-47. doi:10.4239/wjd.v1.i2.36
Slining, M. M., Herring, A. H., Popkin, B. M., Mayer-Davis, E. J., & Adair, L. S. (2013). Infant BMI trajectories are associated with young adult body composition. *J Dev Orig Health Dis, 4*(1), 56-68. doi:10.1017/S2040174412000554
Song, Y., Joung, H., Engelhardt, K., Yoo, S. Y., & Paik, H. Y. (2005). Traditional v. modified dietary patterns and their influence on adolescents' nutritional profile. *Br J Nutr, 93*(6), 943-949. doi:10.1079/bjn20051435
Sotres-Alvarez, D., Herring, A. H., & Siega-Riz, A. M. (2010). Latent Class Analysis Is Useful to Classify Pregnant Women into Dietary Patterns. *The Journal of Nutrition, 140*(12), 2253-2259. doi:10.3945/jn.110.124909
Spinrad, T. L., Eisenberg, N., & Gaertner, B. M. (2007). Measures of Effortful Regulation for Young Children. *Infant Ment Health J, 28*(6), 606-626. doi:10.1002/imhj.20156
Tein, J. Y., Coxe, S., & Cham, H. (2013). Statistical Power to Detect the Correct Number of Classes in Latent Profile Analysis. *Struct Equ Modeling, 20*(4), 640-657. doi:10.1080/10705511.2013.824781
The, N. S., Suchindran, C., North, K. E., Popkin, B. M., & Gordon-Larsen, P. (2010). Association of adolescent obesity with risk of severe obesity in adulthood. *JAMA, 304*(18), 2042-2047. doi:10.1001/jama.2010.1635
Togo, P., Heitmann, B. L., Sorensen, T. I., & Osler, M. (2003). Consistency of food intake factors by different dietary assessment methods and population groups. *Br J Nutr, 90*(3), 667-678. doi:10.1079/bjn2003943
U.S. Department of Agriculture and U.S. Department of Health and Human Services. Dietary Guidelines for Americans, 2020-2025. *9th Edition. Available at DietaryGuidelines.gov.* (December 2020.).

VanKim, N. A., Larson, N., & Laska, M. N. (2012). Emerging adulthood: a critical age for preventing excess weight gain? *Adolesc Med State Art Rev, 23*(3), 571-588.
Ventura, A. K., Loken, E., & Birch, L. L. (2009). Developmental trajectories of girls' BMI across childhood and adolescence. *Obesity (Silver Spring), 17*(11), 2067-2074. doi:10.1038/oby.2009.123
Viner, R. M., Costa, S., & Johnson, W. (2019). Patterns of BMI development between 10 and 42 years of age and their determinants in the 1970 British Cohort Study. *J Epidemiol Community Health, 73*(1), 79-85. doi:10.1136/jech-2018-211051
Walsh, E. I., Shaw, J., & Cherbuin, N. (2018). Trajectories of BMI change impact glucose and insulin metabolism. *Nutr Metab Cardiovasc Dis, 28*(3), 243-251. doi:10.1016/j.numecd.2017.12.003
Wedin, W. K., Diaz-Gimenez, L., & Convit, A. J. (2012). Prediction of insulin resistance with anthropometric measures: lessons from a large adolescent population. *Diabetes Metab Syndr Obes, 5*, 219-225. doi:10.2147/DMSO.S33478
Weihrauch-Bluher, S., Schwarz, P., & Klusmann, J. H. (2019). Childhood obesity: increased risk for cardiometabolic disease and cancer in adulthood. *Metabolism, 92*, 147-152. doi:10.1016/j.metabol.2018.12.001
Weng, T. T., Hao, J. H., Qian, Q. W., Cao, H., Fu, J. L., Sun, Y., . . . Tao, F. B. (2012). Is there any relationship between dietary patterns and depression and anxiety in Chinese adolescents? *Public Health Nutr, 15*(4), 673-682. doi:10.1017/S1368980011003077
Wickrama, K. A., Noh, S., & Elder, G. H. (2009). An investigation of family SES-based inequalities in depressive symptoms from early adolescence to emerging adulthood. *Adv Life Course Res, 14*(3). doi:10.1016/j.alcr.2010.04.001
Wideman, L., Calkins, S. D., Janssen, J. A., Lovelady, C. A., Dollar, J. M., Keane, S. P., . . . Shanahan, L. (2016). Rationale, design and methods for the RIGHT Track Health Study: pathways from childhood self-regulation to cardiovascular risk in adolescence. *BMC Public Health, 16*, 459. doi:10.1186/s12889-016-3133-7
Winpenny, E. M., Greenslade, S., Corder, K., & van Sluijs, E. M. F. (2018). Diet Quality through Adolescence and Early Adulthood: Cross-Sectional Associations of the Dietary Approaches to Stop Hypertension Diet Index and Component Food Groups with Age. *Nutrients, 10*(11). doi:10.3390/nu10111585
Wirt, T., Hundsdorfer, V., Schreiber, A., Kesztyus, D., Steinacker, J. M., & Komm mit in das gesunde Boot - Grundschule" - Research, G. (2014). Associations between inhibitory control and body weight in German primary school children. *Eat Behav, 15*(1), 9-12. doi:10.1016/j.eatbeh.2013.10.015
Wright, M., Sotres-Alvarez, D., Mendez, M. A., & Adair, L. (2017). The association of trajectories of protein intake and age-specific protein intakes from 2 to 22 years with BMI in early adulthood. *Br J Nutr, 117*(5), 750-758. doi:10.1017/S0007114517000502
Yuan, Y., Chu, C., Zheng, W. L., Ma, Q., Hu, J. W., Wang, Y., . . . Mu, J. J. (2020). Body Mass Index Trajectories in Early Life Is Predictive of Cardiometabolic Risk. *J Pediatr, 219*, 31-37 e36. doi:10.1016/j.jpeds.2019.12.060
Zhang, J., Wang, H., Wang, Y., Xue, H., Wang, Z., Du, W., . . . Zhang, B. (2015). Dietary patterns and their associations with childhood obesity in China. *Br J Nutr, 113*(12), 1978-1984. doi:10.1017/S0007114515001154

Zhang, T., Xu, J., Li, S., Bazzano, L. A., He, J., Whelton, P. K., & Chen, W. (2019). Trajectories of childhood BMI and adult diabetes: the Bogalusa Heart Study. *Diabetologia, 62*(1), 70-77. doi:10.1007/s00125-018-4753-5

APPENDIX A: SUPPLEMENTAL TABLES AND FIGURES FOR CHAPTER II

Table A1. Model constraints and Fit Indices for Latent Class Growth and Growth Mixture BMI Trajectory Models without Covariates

# of Classes	Model Type*	Model Constraints**	AIC	BIC	Entropy	LMR p-value	C1 n(%)	C2 n(%)
2	LCGA	Var(i)=Var(s)=Var(q)=0	8463.62	8529.54	0.926	0.039	296(83)	61(17)
2	GMM	None	7498.98	7599.80	0.849	0.000	312(87)	45(13)
2	GMM	Var(q)=0 in both classes	7546.42	7631.73	0.813	0.035	304(85)	53(15)
2	**GMM**	C1: Var(q)=0; C2: None	**7471.33**	**7568.27**	**0.720**	**0.000**	**272(76)**	**85 (24)**

* LCGA (Latent class growth analysis): variance of intercept, linear, and quadratic terms forced to zero; GMM (Growth mixture model): variance of intercept, linear, and quadratic terms allowed to vary and covary, unless constrained

** Var(i)=0: variance of intercept constrained to 0; Var(s)=0: variance of linear term constrained to 0; Var(q)=0: variance of quadratic term constrained to 0

Table A2. Fit Indices for GMM Model Deriving BMI Trajectories at Increasing Number of Latent Classes and with Significant Covariates

# of Classes	Model Constraints*	AIC	BIC	Entropy	LMR p-value	C1 n(%)	C2 n(%)	C3 n(%)	C4 n(%)
2	C1: Var(q)=0; C2: None	7471.33	7568.27	0.720	0.000	272(76)	85 (24)	N/A	N/A
3	C1: Var(q)=0; C2, C3: None	**7426.91**	**7550.99**	**0.711**	**0.041**	**234(65)**	**102(29)**	**21(6)**	**N/A**
4	C1: Var(q)=0; C2, C3, C4: None	7499.33	7650.56	0.860	0.540	272(76)	85(24)	0(0)	0(0)
3	C1: Var(q)=0; C2, C3: None+cov**	7235.98	7397.89	0.703	0.104	225(64)	101(29)	23(7)	N/A
2	**C1: Var(q)=0; C2: None+cov****	**7274.83**	**7402.05**	**0.741**	**0.000**	**272(78)**	**77(22)**	N/A	N/A

* Var(q)=0: variance of quadratic term constrained to 0

** cov = covariates significantly associated with class membership (race and socioeconomic status)

Table A3. Multinomial Logistic Regression Results for Predictors of Class Membership for 3-class Unconditional GMM

Effect	Estimate	Standard Error	DF	Wald Chi-Square	Pr > ChiSq
Race	-0.880	0.2376	1	13.7169	0.0002*
Sex	-0.189	0.2313	1	0.6701	0.4130
SES	0.020	0.0108	1	3.3251	0.0682*

* Significance threshold set at p<0.10

Table A4. Logistic Regression Results for Predictors of Class Membership for 2-class Unconditional GMM

Effect	Estimate	Standard Error	DF	Wald Chi-Square	Pr > ChiSq
Race	-0.977	0.2679	1	13.3189	0.0003*
Sex	-0.262	0.2673	1	0.9617	0.3267
SES	0.025	0.0124	1	4.0302	0.0447*

* Significance threshold set at p<0.10

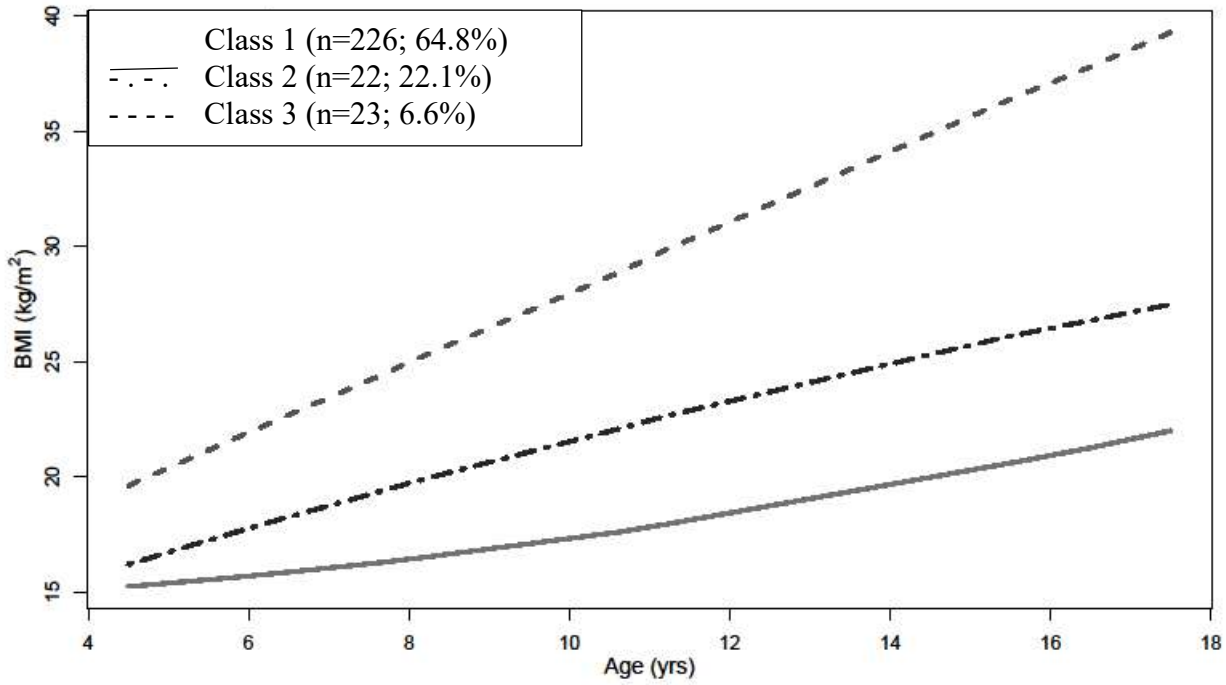

Figure A1. Longitudinal BMI Trajectories for 3-class Conditional GMM

Table A5. Regression coefficients[1] (95% Confidence Intervals) for Normal to Overweight Transition Group, Excluding Participants Classified in the Stable Obese Group by the 3-class GMM

Parameter	Model 1		Model 2[2]		Model 3[3]		Model 4[4]	
	b(95%CI) [n]	p-value	b(95%CI) [n]	p-value	b(95%CI) [n]	p-value	b(95%CI) [n]	p-value
% BF	8.39 (4.24, 12.54) [188]	<0.001	9.04(5.63, 12.46) [186]	<0.001	2.12(-0.518, 4.76) [184]	0.115	N/A	N/A
Fasting Glucose (mg/dL)[5]	2.58(-3.22, 8.38) [205]	0.381	3.11(-2.82, 9.04) [201]	0.302	1.219(-5.02, 7.43) [201]	0.703	-0.03(-6.65, 6.59) [177]	0.992
Fasting Insulin (μIU/mL)[5]	40.3(8.75, 71.77) [189]	0.013	41.1(8.94, 73.25) [0.186]	0.013	26.5(-7.56, 60.50) [186]	0.127	44.5(7.94, 81.12) [163]	0.017
HOMA-IR[5]	43.1(10.65, 75.47) [187]	0.012	44.2(11.21, 77.22) [184]	0.009	27.6(-7.26, 62.41) [184]	0.120	45.9(8.48, 83.27) [162]	0.017
WC (cm)	11.62 (7.13, 16.11) [215]	<0.001	11.56(7.10, 16.03) [211]	<0.001	N/A	N/A	4.99(1.31, 8.66) [184]	0.008

[1] Stable Normal Weight group is the referent class. Regression coefficient for %BF and WC outcomes is the mean difference between the two classes. The reported regression coefficients for fasting glucose, fasting insulin, and HOMA-IR were multiplied by 100 and are interpreted as the percentage of change in the outcome for being in the Normal to Overweight Transition group compared to the referent Stable Normal Weight group since fasting glucose, fasting insulin, and HOMA-IR were natural log transformed.

[2] Adjusted for race, sex, socioeconomic status.

[3] Adjusted for race, sex, socioeconomic status, and waist circumference at young adulthood (WC).

[4] Adjusted for race, sex, socioeconomic status, and body fat percentage at young adulthood (% BF).

APPENDIX B: SUPPLEMENTAL TABLES AND FIGURES FOR CHAPTER IV

Table B1. Collapsed Food Categories, Excluded Food Items, and Corresponding NDSR Food Items and Groups

Collapsed Category	Food Item Description	NDSR Variable	Original NDSR Food Group
Sugar-Sweetened Beverages	Coffee, Sweetened	BVS0100	Beverages
	Tea, Sweetened	BVS0500	
	Water - Sweetened	BVS0600	
	Fruit Drink	BVS0300	
	Soft Drink	BVS0400	
	Sports Drinks/Meal Replacement	BVS0700	
	Milk Beverage, Sweetened without Dry Milk	SWT0600	Sweets
Reduced calorie/Noncaloric Beverages	Coffee, Unsweetened	BVU0100	Beverages
	Tea, Unsweetened	BVU0400	
	Tea, Artificially Sweetened	BVA0500	
	Water	BVU0500	
	Water, Artificially Sweetened	BVA0600	
	Fruit Drinks, Artificially Sweetened	BVA0300	
	Soft Drinks, Unsweetened	BVU0300	
	Soft Drinks - Artificially Sweetened	BVA0400	
	Nondairy Supplement, Unsweetened	BVU0600	
	Nondairy Supplement, Artificially Sweetened	BVA0700	
Alcoholic Beverages	Beer/Ale	BVE0100	Beverages
	Wine	BVE0200	
	Distilled Liquor	BVE0300	
	Cordial/Liqueur	BVE0400	
Full Fat Dairy	Cheese, Full Fat	DCF0100	Dairy/Nondairy Alternatives
	Milk, Whole	DMF0100	
	Flavored Milk, Whole	DMF0200	
	Yogurt, Sweetened Whole Milk	DYF0100	
	Yogurt, Unsweetened Whole Milk	DYF0200	
Reduced/Fat Free Dairy	Cheese, Reduced Fat	DCR0100	Dairy/Nondairy Alternatives
	Cheese, Fat Free	DCL0100	
	Milk, 2%	DMR0100	
	Milk, Low Fat/Fat Free	DML0100	
	Flavored Milk, Reduced Fat	DMR0200	
	Flavored Milk, Low Fat/Fat Free	DML0200	
	Flavored Dry Milk, Fat Free	DML0300	
	Yogurt, Sweetened Low Fat	DYR0100	
	Yogurt, Sweetened Fat Free	DYL0100	

Collapsed Category	Food Item Description	NDSR Variable	Original NDSR Food Group
	Yogurt, Artificially Sweetened Low Fat	DYR0200	
	Yogurt, Unsweetened Fat Free	DYL0200	
	Dairy-based Meal Replacement	DOT0500	
	Dairy-based Meal Replacement, Artificially Sweetened	DOT0600	
Nondairy Substitutes	Cheese - Nondairy	DCN0100	Dairy/Nondairy Alternatives
	Milk - Nondairy	DMN0100	
	Cream - Nondairy	FCN0100	Fat
Full Fats	Butter	FAF0100	Fat
	Cream	FCF0100	
	Oil	FOF0100	
	Margarine	FMF0100	
	Shortening	FSF0100	
	Salad Dressing, Regular	FDF0100	
	Avocado/Guacamole	FRU0500	Fruit
Reduced Fats	Butter, Reduced Fat	FAR0100	Fat
	Cream, Reduced Fat	FCR0100	
	Cream, Low Fat/Fat Free	FCL0100	
	Margarine, Low Fat	FMR0100	
	Salad Dressing, Low Fat	FDR0100	
Fruit Juice	Juice, Citrus	FRU0100	Fruit
	Juice, Non-citrus	FRU0200	
Fruits	Whole Fruit, Citrus	FRU0300	Fruit
	Whole Fruit, Non-citrus	FRU0400	
	Fried Fruit, Not Breaded	FRU0600	
	Fruit-based Savory Snack	FRU0700	
Whole Grains and Starches	Non-Grain Flour	MSC0700	Miscellaneous
	Whole Grain Mixes	GRW0100	Grains
	Pasta, Whole Grain	GRW0500	
	Crackers, Whole Grain	GRW0400	
	Crackers, Some Whole Grain	GRS0400	
	Cereal, Unsweetened Whole Grain	GRW0600	
	Cereal, Sweetened Whole Grain	GRW0700	
	Cereal, Sweetened Some Whole Grain	GRS0700	
	Bread, Whole Grain Loaf	GRW0200	
	Bread, Some Whole Grain	GRS0200	
	Other Bread/Tortillas, Whole Grain	GRW0300	
	Other Bread/Tortillas, Some Whole Grain	GRS0300	
Refined Grains	Refined Grain Mixes	GRR0100	Grains
	Pasta, Refined Grain	GRR0500	
	Crackers, Refined Grain	GRR0400	
	Cereal, Unsweetened Refined Grain	GRR0600	
	Cereal, Presweetened Refined Grain	GRR0700	
	Bread, Refined Grain Loaf	GRR0200	

Collapsed Category	Food Item Description	NDSR Variable	Original NDSR Food Group
	Other Bread/Tortillas, Refined Grain	GRR0300	
Snacks	Potato Chips	FMC0100	Fat
	Chips, Whole Grain	GRW0900	Grain
	Chips, Refined Grain	GRR0900	
	Chips, Some Whole Grain	GRS0900	
	Snack Bar, Whole Grain	GRW1000	
	Snack Bar, Some Whole Grain	GRS1000	
	Snack Bar, Refined Grain	GRR1000	
	Popcorn	GRW1100	
	Flavored Popcorn	GRW1200	
Desserts	Cookies/Cakes, Whole Grain	GRW0800	Grains
	Cookies/Cakes, Some Whole Grain	GRS0800	
	Cookies/Cakes, Refined Grain	GRR0800	
	Frozen Dessert, Dairy	DOT0100	Dairy/Nondairy Alternatives
	Frozen Dessert, Nondairy	DOT0200	
	Pudding/Other Dairy Dessert	DOT0300	
	Miscellaneous Dessert	MSC0600	Miscellaneous
	Candy, Chocolate	SWT0100	Sweets
	Candy, Non-chocolate	SWT0200	
	Sugar	SWT0400	
	Syrup	SWT0500	
	Frosting/Glaze	SWT0300	
	Sweet Sauce, Regular	SWT0700	
	Sweet Sauce, Reduced Fat/Fat Free	SWT0800	
Starchy Vegetables	White Potatoes[2]	VEG0400	Vegetables
	Other Starchy Vegetables	VEG0450	
Non-Starchy Vegetables	Green Vegetables	VEG0100	Vegetables
	Yellow Vegetables	VEG0200	
	Tomatoes	VEG0300	
	Vegetable Juice	VEG0500	
	Other Vegetables	VEG0600	
Fried Vegetables	Fried Potatoes	VEG0800	Vegetables
	Fried Vegetables, Breaded[1]	VEG0900	
Vegetable Protein	Beans/Legumes	VEG0700	Vegetables
	Nuts and Seeds	MOF0500	Meat/Protein
	Nut and Seed Butters	MOF0600	
	Meat Alternatives	MOF0700	
Lean Meats	Poultry, Lean	MPL0100	Meat/Protein
	Beef, Lean	MRL0100	
	Fresh Pork, Lean	MRL0400	
	Lamb, Lean	MRL0300	
	Fish, Lean	MFL0100	
	Shellfish	MSL0100	
	Cold Cuts, Lean	MCL0100	

Collapsed Category	Food Item Description	NDSR Variable	Original NDSR Food Group
	Eggs	MOF0300	
Full Fat, Fried, and Cured Meats	Poultry	MPF0100	Meat/Protein
	Fried Chicken	MPF0200	
	Beef	MRF0100	
	Fresh Pork	MRF0400	
	Lamb	MRF0300	
	Game	MRF0500	
	Fish, Fresh and Smoked	MFF0100	
	Fish, Fried/Fast Food	MFF0200	
	Shellfish – Fried/Fast Food	MSF0100	
	Cold cuts – Full Fat	MCF0100	
	Cured Pork	MCF0200	
	Cured Pork, Lean	MCL0200	
Condiments/Other	Gravy, Regular	MSC0100	Miscellaneous
	Gravy, Reduced Fat/Fat Free	MSC0200	
	Sauces, Full Fat	MSC0300	
	Sauces, Reduced Fat	MSC0400	
	Pickled Foods	MSC0500	
	Soup Broth	MSC0800	
	Sugar Substitute	MSC1200	
Excluded Food Items	Coffee Substitute, Sweetened	BVS0200	Beverages
	Coffee Substitute, Unsweetened	BVU0200	
	Coffee, Artificially Sweetened	BVA0100	
	Coffee Substitutes, Artificially Sweetened	BVA0200	
	Beer, Non-alcoholic	BVO0100	
	Light Beer, Non-alcoholic	BVO0200	
	Yogurt, Nondairy	DYN0100	Dairy/Nondairy Alternatives
	Pudding, Artificially Sweetened	DOT0400	
	Flavored Milk Powder, Fat Free	DML0400	
	Infant Formula	DOT0700	
	Infant Formula, Nondairy	DOT0800	
	Meat-based Savory Snack	FMC0200	Fats
	Baby Food, Whole Grain	GRW1300	Grains
	Baby Food, Some Whole Grain	GRS1300	
	Baby Food, Refined Grain	GRR1300	
	Grains, Flour, Mixes, Whole Grain	GRS0100	
	Pasta, Some Whole Grain	GRS0500	
	Cereal, Some Whole Grain	GRS0600	
	Veal	MRF0200	Meat/Protein
	Veal, Lean	MRL0200	
	Organ Meats	MOF0100	
	Baby Food, Meat Mixture	MOF0200	
	Egg Substitute	MOF0400	

Collapsed Category	Food Item Description	NDSR Variable	Original NDSR Food Group
	Baby Food, Dessert	MSC0900	Miscellaneous
	Baby Food, Miscellaneous	MSC1000	
	Flavored Milk Powder, Artificially Sweetened	MSC1100	

[1] Excludes fried potatoes

Table B2. Odds Ratios[a] for Balanced versus Unbalanced Pattern

Food Category	Odds Ratio (SE)	p-value
Sugar-Sweetened Beverages		
Consumers vs. Non-Consumers	0 (0)[b]	1.000
High Consumers versus Low and Non-Consumers	0.18 (2.998)	0.131
Reduced Calorie/Noncaloric Beverages		
High Consumers versus Low and Non-Consumers	16.66 (0.045)	0.000
Alcoholic Beverages		
Consumers versus Non-Consumers	0 (0)[b]	1.000
Full Fat Dairy		
High Consumers versus Low and Non-Consumers	1.04 (0.455)	0.930
Reduced/Fat Free Dairy		
High Consumers versus Low and Non-Consumers	2.08 (0.232)	0.025
Nondairy Substitutes		
Consumers versus Non-Consumers	11.11 (0.073)	0.000
Full Fats		
High Consumers versus Low and Non-Consumers	0.88 (0.596)	0.825
Reduced Fats		
Consumers versus Non-Consumers	1.59 (0.241)	0.130
High Consumers versus Low and Non-Consumers	3.13 (0.181)	0.000
Fruits		
Consumers versus Non-Consumers	4.17 (0.108)	0.000
High Consumers versus Low and Non-Consumers	5.00 (0.091)	0.000
Fruit Juice		
Consumers versus Non-Consumers	0.37 (1.247)	0.178
High Consumers versus Low and Non-Consumers	0.23 (2.708)	0.225
Whole Grains and Starches		
Consumers versus Non-Consumers	1.69 (0.318)	0.200
High Consumers versus Low and Non-Consumers	6.25 (0.113)	0.000
Refined Grains		
High Consumers versus Low and Non-Consumers	0.870 (0.601)	0.807
Snacks		
Consumers versus Non-Consumers	0.68 (0.661)	0.490
High Consumers versus Low and Non-Consumers	2.00 (0.266)	0.060
Desserts		
High Consumers versus Low and Non-Consumers	0.85 (0.645)	0.783

Starchy Vegetables		
Consumers versus Non-Consumers	0.966 (0.432)	0.935
High Consumers versus Low and Non-Consumers	1.25 (0.363)	0.588
Non-Starchy Vegetables		
High Consumers versus Low and Non-Consumers	5.56 (0.079)	0.000
Fried Vegetables		
Consumers versus Non-Consumers	0.10 (5.730)	0.111
High Consumers versus Low and Non-Consumers	0.08 (10.100)	0.229
Vegetable Protein		
Consumers versus Non-Consumers	1.23 (0.352)	0.584
High Consumers versus Low and Non-Consumers	2.56 (0.190)	0.001
Lean Meats		
High Consumers versus Low and Non-Consumers	1.92 (0.248)	0.055
Full Fat, Fried, and Cured Meats		
High Consumers versus Low and Non-Consumers	0.28 (1.656)	0.124
Condiments/Other		
Consumers versus Non-Consumers	0.54 (1.097)	0.432
High Consumers versus Low and Non-Consumers	1.12 (0.393)	0.788

[a] Logits for corresponding odds ratios computed via proportional odds
[b] Estimate forced to zero due to insufficient sample size per group