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Delay Discounting and Food Reinforcement in Youth of Color: A Cluster Analysis

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Delay Discounting and Food Reinforcement in Youth of Color: A Cluster Analysis

A Thesis

Presented in

Partial Fulfillment of the

Requirements for the Degree of

Master of Arts

By

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Thesis Committee

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Biography

The author was born in Illinois in May 1994. Bernardo graduated from James B. Conant High School, Hoffman Estates, IL in 2012. Bernardo received his Bachelor of Arts from DePaul University in 2016.

Table of Contents

Thesis Committee.....	ii
Acknowledgements.....	iii
Biography.....	iv
List of Tables and Figures.....	vii
Abstract.....	1
Introduction.....	2
Pediatric Obesity.....	2
Diet Quality.....	2
Behavioral Economic Theory.....	3
Relative Reinforcing Value of Food	3
Delay Discounting.....	3
The Reinforcing Pathology Model.....	3
Rationale.....	4
Method.....	5
Participants.....	5
Recruitment.....	5
Procedure.....	6
Measures.....	6
Computer Task.....	6
Delay Discounting.....	7
Relative Reinforcing Value of Food.....	7
Meal Diet Quality.....	8
Child BMI z-score.....	9
Preliminary Analyses.....	9
Analytic Plan.....	10
Results.....	12

Descriptive Statistics.....	12
Cluster Descriptions.....	12
Effect Size.....	13
Discussion.....	13
Limitations.....	16
Future Directions.....	17
References.....	20
Tables.....	26
Figures.....	32
Appendix A: Original Thesis Proposal.....	37

List of Tables

Table 1. Sample Demographics.....	26
Table 2. Means and Standard Deviations across Clusters.....	27
Table 3. Correlations.....	28
Table 4. Cluster ANOVA Comparisons.....	29
Table 5. Effect Sizes and their Confidence Intervals between Clusters on HEI-2015.....	30
Table 6. Effect Sizes and their Confidence Intervals between Clusters on kcal.....	30
Table 7. Effect Sizes and their Confidence Intervals between Clusters on zBMI.....	31

List of Figures

Figure 1. Dendrogram using Ward Linkage.....	32
Figure 2. Histogram of Delay Discounting Variable.....	33
Figure 3. Average BMI z-Score Across Clusters.....	34
Figure 4. Average kcal Value Across Clusters.....	35
Figure 5. Average Diet Quality Value Across Clusters.....	36

Abstract

Pediatric obesity within the United States continues to be national health concern. Children of color are systemically impacted by obesity. Behavioral Economics (BE) provides a theoretical framework for understanding what social, psychological, and cultural factors impact decision making and food consumption. BE posits that poor executive control (i.e., impulsivity) and relative reinforcing value of food (RRV_{food}) are two main behavioral components that predict consumption habits. These constructs are poorly understood among children from non-white backgrounds. The current study aimed to 1) identify patterns of impulsivity and food reinforcement within a diverse sample of 88 elementary school children and 2) determine whether these patterns vary by BMI z-score, calorie intake, and meal diet quality. Hierarchical cluster analyses revealed a 4-cluster solution with students' RRV_{food} and DD varying across clusters (Cluster 1: Low DD/Low RRV_{food} ; Cluster 2: High DD/Low RRV_{food} ; Cluster 3: Low DD/High RRV_{food} ; Cluster 4: High DD/High RRV_{food} (highest risk profile). Surprisingly, BMI z-score, caloric intake, and meal diet quality did not vary significantly by cluster. Findings provide support for exploring the reinforcing pathology model among youth of color and may suggest future interventions focus on impulsivity and food reinforcement, particularly among children who score highly on both measures.

Keywords: Childhood Obesity; Reinforcing Pathology Model; Delay Discounting; Relative Reinforcing Value of Food; Behavioral Economics

Delay Discounting and Food Reinforcement in Youth of Color: A Cluster Analysis

The prevalence of childhood obesity in the United States is 18.5%, with obesity systemically impacting populations of color (25.8% among Hispanic children and 22% among Black children compared to 14.1% among non-Hispanic White children) (National Center for Health Statistics, 2017). These inequities are salient because obesity is associated with the development of numerous chronic health conditions such as cardiovascular disease, various cancers, diabetes, asthma and sleep apnea, musculoskeletal discomfort, depression, anxiety, and low self-esteem (Center for Disease Control and Prevention [CDC], 2018).

Extensive research has been conducted to determine which factors contribute to childhood obesity. Currently, the CDC (2018) recognizes multiple contributing factors including genetics, diet, community characteristics, sleep patterns, and level of physical activity. Some of these factors are likely compounded by systemic oppression. For instance, access to resources (i.e., parks and fresh produce) are often limited in neighborhoods systemically impacted by racism and oppression (Braveman et al., 2011; Braveman & Gottlieb, 2014). Although the causes of obesity are complex, diet has been shown to be one of the most proximal and influential regarding weight gain (Hu et al., 2016; Jennings et al., 2011; Niemeier et al., 2006; Sahoo et al., 2015). In a recent review looking at the causes and consequences of childhood obesity, Sahoo and colleagues (2015) stated that diets that include large portions of fast food, sugary beverages, and snack foods have been associated with weight gain. These foods tend to be of poorer diet quality and contribute to excessive caloric intake when consumed. Understanding what drives eating behavior through theoretical models may better inform the development of effective and sustainable obesity prevention and treatment interventions, particularly among children who need them the most.

Behavioral Economic Theory (BE) describes how psychological and cognitive states and cultural and social factors influence decision making among individuals (Camerer & Loewenstein, 2003) and has been applied to eating behavior and obesity. Two BE-relevant constructs, the reinforcing value of food (RRV_{food} ; Best et al., 2012), or how much work an individual is willing to engage in to acquire a reward when given alternatives (Epstein et al., 2018; Epstein et al., 2007) and Delay Discounting (DD), a construct that identifies behavioral patterns of impulsivity), are particularly important to consider as they relate to food overconsumption and obesity. The *reinforcing pathology model*, sometimes referred to as the reinforcer pathology model or reinforcement pathology model (Bickel et al., 2014; Francis & Susman, 2009; Temple et al., 2008), describes how these two constructs interact to predict diet and weight status. Specifically, the model posits that there is an interaction between an individual's motivation (RRV_{food}) and executive function processes (DD) that can lead to overeating. Energy dense foods have been shown to be significantly more rewarding for individuals who have obesity compared to their counterparts of normal weight status (Temple et al., 2008). In addition to reinforcement, the reinforcing pathology model focuses on executive functioning and an individual's ability to self-regulate. The model states that higher levels of impulsivity will strengthen the relationship between reinforcement and consumption. This concept is noteworthy given that children and adults who have obesity tend to display higher levels of impulsivity compared to their leaner counterparts (Amlung et al., 2016; Bickel, 2014). In combination, those who are highly reinforced by calorie-dense food and have difficulty delaying rewards are predicted to be at greatest risk of overconsumption and obesity.

Previous research has noted that there is a need for studies exploring both DD and RRV_{food} among children (Best et al., 2012). It has also been noted that the relationship between

food reinforcement and ability to delay gratification “may be the behavioral phenotype that may be most associated with high energy intake” (Epstein et al., 2010). Despite this abundant research on DD and RRV_{food} , much of it has been conducted among children seven and older and white children from higher socioeconomic backgrounds (Staubitz et al., 2018). An important first step to exploring the reinforcing pathology model in marginalized youth is to first determine how RRV_{food} and DD vary across children using exploratory person-centered approaches. Identifying clusters of children based on scores on these variables may inform future hypothesis-testing approaches within this population.

Factors that influence children’s eating habits, behaviors, and intake at school are especially important; however, much of the existing literature describes research that utilize labs to conduct their studies rather than real world settings. This limitation is important to note considering children are seldom in these controlled settings when making choices around food. Therefore, more research is needed in children’s natural settings where food consumption is most common. Among systemically oppressed populations, exploring food choice and consumption at home or in other community settings may be challenging due to limited access to foods high in diet quality (Braveman et al., 2011; Braveman & Gottlieb, 2014). Because of the Healthy, Hunger Free Kids Act of 2010, which aimed to reduce food insecurity and aligned school meals with the Dietary Guidelines for Americans, children from low-income families have access to healthy foods at school, making the school setting an ideal setting to investigate dietary intake within this population (Schwartz & Wootan, 2019). The goal of the present study is to use a person-centered approach (hierarchical cluster analysis) to:

- 1) Describe patterns of mean RRV_{food} and DD scores within a diverse sample of elementary school children.

- 2) Determine whether these identified clusters vary by dietary and weight outcomes (i.e., BMI z-score, meal diet quality, and calorie intake).

These findings will help inform our understanding of the relationship between motivation (reinforcement) and executive functioning (impulsivity) among marginalized, urban youth. Further, this study will address an important gap in the literature given that these children are disproportionately affected by obesity but are often underrepresented in pediatric obesity studies in this area.

Method

Participants

Participants consisted of primary school aged children in grades 1-4. In total, 88 students (28 -1st graders, 24 - 2nd graders, 15 - 3rd graders, and 21 - 4th graders) participated.

Demographically, this student sample was 51.1% female and 77.3% Hispanic/Latinx, 10.2% African-American, and 12.5% Other. Of the 11 caregivers who marked “Other”, 6 noted that their child was Latinx and Non-Hispanic Black, 2 noted that their child was Latinx, Non-Hispanic Black, and Non-Hispanic White, and 3 noted that their child was Latinx and Non-Hispanic White.

Recruitment

Two strategies were utilized for recruitment: 1) Informative folders containing flyers and blank consent forms were sent home with all children; and 2) research assistants attended school orientation day and report card pick up day and passed out information folders to interested caregivers directly. Interested caregivers returned signed consent forms to their child’s school that were later collected by a research assistant. Flyers and blank consent forms within folders were in English and Spanish.

Procedure

Children who received caregiver permission participated in the study during their elective classes (music, dance, gym, technology). Prior to participation, children were also asked to provide assent. Following the assent process, trained research assistants (RA) administered the delay discounting (DD) and Relative Reinforcing Value of Food (RRV_{food}) tasks with the children. Each measure was administered on a laptop computer. Anthropometric data was also collected using a research-grade Hopkins stadiometer to measure height (cm) and a Tanita digital scale to measure weight (lb). After surveys and anthropometric data were completed, the research team returned to the school to measure lunchroom food consumption. Data collection on lunchroom food consumption occurred in April 2018. On these days, teachers were given a list containing the names of their students who were enrolled in the study and asked to place these children at the front of the line when bringing their class down for lunch. Upon entering the lunchroom, a RA recorded the child's ID on their paper lunch tray with a food safe marker. After the children selected their food, another RA captured a photo of the lunch tray at the end of the line. Children were instructed to raise their hand once they were finished with their lunch. Once a child raised their hand, photos of the child's post-consumption plate were taken by RAs.

Measures

Computer Task. The computer task began by having children rank order their favorite foods from a list of unhealthy and healthy options that were typically served in the school lunchroom. This list contained common foods (i.e., apples, candy, oranges, cookies, ice cream, celery, etc.). The highest ranked unhealthy and healthy foods were used for the DD and RRV_{food} tasks. Using children's top ranked foods for these measures ensures responses were not

influenced by preference (i.e., if cookies were used for all children, then children who like cookies may respond differently than children who do not like cookies on these measures).

Delayed Discounting (DD). The DD task consisted of nine items that asked the child to pick between an immediate food reward and a delayed food reward (Mischel & Metzner, 1962). The food reward was the food item that was ranked highest by the child. The image of the selected food was shown for each item to help children understand the questions. An example item would be, “Would you rather have one slice of pizza today or two tomorrow?” One pizza slice appeared for the immediate reward option (now) and two slices appeared next to the delayed reward (tomorrow). The delay increased with each item, but the immediate reward is held constant at “today”: one today – two today, one today – two tomorrow, one today – two in five days, one today – two in one week, etc. RAs read each item to all participants and responses were selected (clicked) by the child or the RA, depending on child preference. Steeper delay discount scores indicate higher levels of impulsivity (Best et al., 2012; Kirby & Maraković, 1996). Among child samples, Best and colleagues (2012) found that food DD tasks displayed convergent validity with monetary DD tasks. Likewise, a meta-analysis looking at various self-control measures among children has suggested that there is acceptable convergent validity between DD tasks and other impulsivity measures (Duckworth & Kern, 2011).

Relative Reinforcing Value of Food (RRV_{food}). RRV_{food} consisted of 12 items and assesses the reinforcing value of energy dense food (Goldfield et al., 2004). These items appeared as a list of comparisons between the child’s highest ranked unhealthy food and highest ranked healthy food. For this task, children were asked if they would prefer to click a button (work) a certain number of times for the unhealthy food or healthy food. The number of clicks were held constant for the healthy food but increase in a fixed interval for the unhealthy food

item with each question. The point at which the child no longer prefers to click the button for the unhealthy food, two items in a row, indicates a switch point and the reinforcing value of the unhealthy food. Example items include 20 button presses for a cookie - 20 for an apple, 40 button presses for a cookie – 20 for an apple, 60 button presses for a cookie – 20 for an apple, etc. These items were read by RAs as hypothetical scenarios. Children were asked to press a physical button 20 times to provide perspective for items asking if they would press the button more times for later items. Hypothetical RRV_{food} button press tasks have been validated among adults (Goldfield et al., 2004) and have been used successfully among a child sample (Hill et al., 2009).

Meal Diet Quality. The Nutrition Data System for Research (NDSR) was used to determine the meal diet quality of the consumed portions of each child's lunch. Specifically, each food item from the pre- and post- lunch photos were coded using an 11-point percentage scale ranging from 0% to 100% consumed. The NDSR is a dietary analysis program developed by the University of Minnesota Nutrition Coordinating Center (NCC) and uses the NCC Food and Nutrient Database (includes over 18,000 foods) to calculate the nutritional breakdown (i.e., kcals, grams of fat and sugar consumed, portion of total calories from fruits and vegetables, etc.) of consumed foods (Probst & Tapsell, 2005; Sievert et al., 1989). Individual “menus” were created for each participant containing the coded food items. From these menus, the NDSR was able to calculate a Healthy Eating Index (HEI) score. The HEI is an index of how closely the meal diet quality of consumed food matches the 2010 Dietary Guidelines of America (Guenther et al., 2013). According to Guenther and colleagues (2013), the HEI is a valid and reliable measure of meal diet quality. The NDSR has been used successfully in past research to evaluate fruit and vegetable consumption among children at school (Harrington et al., 2009).

Child BMI z-scores. Height and weight were collected for each participant. Children were asked to remove their shoes, all items from their pockets, and heavy clothing (i.e., sweatshirts or jackets). Height was measured in centimeters using a stadiometer. Weight was measured in pounds using a digital weight scale. Standardized BMI was calculated for each child based on gender- and age-specific growth charts provided by the CDC (Kuczmarski et al., 2002). Growth charts were computed based on normative samples from the 1960s through the 1990s. Syntax for the statistical software STATA, provided by the CDC, was used to calculate the BMI z-scores for our sample.

Preliminary Analyses

DD scores were calculated as the ratio between the total number of immediate reward selections over the number of delayed reward selections. RRV_{food} was calculated as the switch point value or point where children are no longer willing to work for the unhealthy food and switch to the healthy alternative. All data was plotted to assess normality; however, due to skewness across RRV_{food} and DD, data were dichotomized into low (0) and high (1) groups. RRV_{food} was divided using a mean split with values equal to or less than 4.10 comprising the low group and greater than 4.10 comprising the high group. Similarly, low switch points (≥ 2 for high RRV_{food}) have been used in previous studies (Best et al., 2012). Unlike the RRV_{food} variable, the skewed responses to the DD measure accumulated naturally at the low and high ends of the scale with no response data in the belly of the distribution [see Figure 2]. Additionally, 72.7% of the sample scored a 7 or 8 on DD, with 8 being the maximum possible score. Therefore, those who scored less than or equal to 7 were placed into the low group while those who scored an 8 comprised the high group. This decision allowed the dichotomization of the DD variable to be statistically useful by creating more equally sized groups while remaining clinically relevant.

Specifically, the low group indicates that the individual was able to delay an immediate reward for a larger, healthier reward at least once (score of 7) compared to the high group which includes those who chose an immediate unhealthy reward every time (score of 8). These variables have been dichotomized in previous studies (Best et al., 2012) and clustering dichotomized data is suitable for addressing the current research question (Fonseca, 2013). We also conducted initial ANOVAs and t-tests, which revealed no significant differences between demographic variables (i.e., sex, grade, and race/ethnicity) and our predictor variables ($p > .05$).

Analytic Plan

Descriptive statistics were conducted across demographic factors and variables of interest. In order to better identify how DD and RRV_{food} vary among students, hierarchical cluster analysis was used to group cases (students) based on their scores on the DD and RRV_{food} measures. The hierarchical cluster analysis used an agglomeration schedule (bottom-up approach) with each case starting as their own cluster (Bridges, 1966; Ward & Hook, 1961; Ward & Hook, 1963). Cases were then joined with their closest neighbor to create a new, larger cluster (Bridges, 1966; Ward & Hook, 1961; Ward & Hook, 1963). This process was done iteratively until the data was placed into a hierarchy of clusters easily identified using a dendrogram chart [Figure 1] (Bridges, 1966; Ward & Hook, 1961; Ward & Hook, 1963). In order to produce flat clustering, a distance threshold that identified 4 distinct clusters was chosen (Madhulatha, 2012). The agglomeration schedule was produced using the Ward method because it is best for creating comparable sized, and distinct, clusters (Bridges, 1966; Ward & Hook, 1961; Ward & Hook, 1963). This is partly due to Ward's method focusing on the distance between the clusters and the grand mean similar to an ANOVA; emphasizing the differences among clusters (Ward & Hook, 1961; Ward & Hook, 1963). To aid in producing dissimilar

clusters, the method also groups cases in a way that reduces the variance within the overall cluster (Bridges, 1966; Ward & Hook, 1961; Ward & Hook, 1963). Under this method, the case that introduces the least amount of error into a cluster is included (Bridges, 1966; Ward & Hook, 1961; Ward & Hook, 1963). Ward's method has produced one of the better clustering performances within previous binary data studies when compared to nine other methods (Tamasauskas et al., 2012). To measure the distance between clusters, the binary squared Euclidean distance was used because it is suitable for interval data that has been dichotomized (Fonseca, 2013). Similarly, squaring the Euclidean distance places more emphasis on larger distances compared to smaller distances, helping produce discrete clusters (Madhulatha, 2012).

One-way analysis of variance (ANOVA) was used for between-cluster comparisons across continuous parametric variables that were not used as input parameters for creating clusters. Similarly, Chi-square (χ^2) analyses were conducted with categorical demographic variables to assess possible proportional differences between-clusters.

Due to the current study's sample size, Cohen's d values were calculated to measure effect sizes. The effect size statistic is necessary for addressing the current study's sample and achieving a more comprehensive understanding of results. In order to detect statistical significance, appropriately sized and comparable samples are necessary (Sullivan & Feinn, 2012). As noted by Sullivan and Feinn (2012), relying on one statistic such as a p -value is not enough for understanding outcomes. Specifically, a significant p -value is often easily obtained by large sample sizes that inflate a study's statistical power to identify differences (Sullivan & Feinn, 2012). Beyond observing statistical significance (p -value), researchers should also report *substantive* significance (Sullivan & Feinn, 2012). This concept relates to effect sizes which report the magnitude of the differences found between two groups.

Results

Descriptive Statistics

See Table 1 for descriptive statistics. For the overall sample ($n = 88$), mean and standard deviation across variables of interest were: DD ($M = 6.02$, $SD = 2.49$); RRV_{food} ($M = 4.10$, $SD = 4.72$); kcal ($M = 350.41$, $SD = 173.75$); BMI z-score ($M = 0.88$, $SD = 1.17$); HEI-2015 Total ($M = 55.01$, $SD = 10.47$). Weight status categories based on BMI z-scores indicated that 50 percent of the sample qualified as overweight or obese (Underweight = 3; Normal = 40; Overweight = 20; Obese = 24; Missing = 1).

Cluster Descriptions

Low Delay Discounting, Low Relative Reinforcing Value of food (Cluster 1; $n = 45$).

Children belonging to this cluster demonstrated little impulsivity ($M = 5.06$, $SD = 2.37$) and are not highly reinforced by food ($M = 2.22$, $SD = 1.28$). They also had the lowest mean BMI z-score of all of the clusters ($M = 0.80$, $SD = 1.13$).

High Delay Discounting, Low Relative Reinforcing Value of food (Cluster 2; $n = 22$).

Children in this cluster showed similarly low levels of food reinforcement ($M = 1.41$, $SD = 1.05$); however, they demonstrated high impulsivity ($M = 8.00$, $SD = 0.00$).

Low Delay Discounting, High Relative Reinforcing Value of food (Cluster 3; $n = 11$).

Children grouped in this cluster rated low on impulsivity ($M = 4.88$, $SD = 2.95$) and were highly reinforced by food ($M = 11.36$, $SD = 5.39$).

High Delay Discounting, High Relative Reinforcing Value of food (Cluster 4; $n = 9$).

Children within this final cluster displayed high levels of impulsivity ($M = 8.00$, $SD = 0.00$) and food reinforcement ($M = 11.22$, $SD = 4.71$). Mean kcal consumption ($M = 438.45$, $SD = 233.25$) and BMI z-score ($M = 1.03$, $SD = 0.76$) were the highest in this cluster [see Table 2].

There were no significant proportional differences ($p > .05$) in sex, grade, and race or ethnicity across clusters. Regarding outcome variables, no significant difference was detected for HEI-2015 Total score $F(3,76) = 1.56, p = .207$; kcal value $F(3,76) = .999, p = .398$; or BMI z-score $F(3,82) = .156, p = .9.25$ [see Table 3]. One student did not have complete data for DD and RRV_{food} and was excluded from the cluster analysis.

Effect Size

The magnitude of mean differences found between clusters 2 and 3 ($d = .807, 95\% \text{ CI } [.0338 - 1.5802]$) and 3 and 4 ($d = -.923, 95\% \text{ CI } [-1.8699 - .0244]$) on HEI-2015 were large. Similarly, the magnitude of mean differences found between clusters 1 and 4 ($d = -.586, 95\% \text{ CI } [-1.3198 - 0.1486]$) and 3 and 4 ($d = -.656, 95\% \text{ CI } [-1.5809 - .268]$) on kcal were medium. Regarding BMI z-Score, no medium or large differences were found between any combination of clusters. See tables 5-7 for effect sizes.

Discussion

Previous research has established links between RRV_{food} , DD, and obesity but no research to date has used a person-centered approach to identify patterns of RRV_{food} and DD within a sample of children of low-income in a school-based real-world setting. We used hierarchical cluster analysis to group cases (students) based on their scores on the DD and RRV_{food} measures and identified four distinct clusters. Cluster 1 was comprised of students who were not highly reinforced by food and had lower levels of DD. This first cluster also had the lowest average BMI z-score compared to the other three clusters (but the difference was not statistically significant). The other three clusters included students who were high on one or both of the BE variables. This pattern suggests that being highly reinforced by food and/or exhibiting high levels of impulsivity may be related to higher weight [see Figure 3].

Cluster 2 was comprised of students who were not highly reinforced by food but had relatively higher DD scores. This higher level of DD may explain changes in kcal consumption and BMI z-score between clusters 1 and 2 [see Figures 3 and 4]. Specifically, children in cluster 2 consumed more calories compared to cluster 1. This difference follows trends from previous research showing higher impulsivity relating to greater food consumption and weight status (Best et al., 2012). It is important to note that Cluster 2 followed nutritional guidelines better than cluster 1 (had higher HEI-2015 Total scores, but the difference was not significant). Given that all foods served in schools align with the Dietary Guidelines for Americans, consuming more food (quantity) is associated with closer adherence to those guidelines and thus, higher meal diet quality. Therefore, although it might seem counterintuitive that higher calorie intake would vary positively with meal diet quality in other contexts, this interpretation is logical in the school environment.

Cluster 3 describes children who are low on DD but highly reinforced by food. This third cluster had the poorest meal diet quality (lowest HEI-2015 Total) and lowest number of calories consumed but was not statistically different from the other Clusters [see Figures 4 and 5]. Again, this trend can likely be explained by the fact that the school meals are proportioned based on guidelines such that eating the whole meal helps students better adhere to the nutritional recommendations. Although Cluster 3 students were highly reinforced by food, their ability to better manage impulses may be a factor for understanding why there is a non-statistically significant pattern of lower BMI z-scores on average, and consumed less calories, compared to Cluster 2 [see Figure 3]. This trend maps onto previous research that suggests impulsivity is a stronger predictor of food consumption and weight status compared to how reinforced someone is by food (Best et al., 2012).

Finally, Cluster 4 represents those individuals who had higher DD scores and were highly reinforced by food. Compared to all other clusters, children belonging to the fourth cluster had the highest BMI z-score on average, though not significantly different from the other clusters [see figure 3]. Despite no clinical significance between clusters, BMI z-scores still allow us to make comparisons between children in our sample and a national normed sample (Kuczmarski et al., 2002). It is noteworthy that children who were both highly impulsive and highly reinforced by food weighed greater than one standard deviation above the average weight for children their same age and gender. Similarly, Cluster 4 displayed a pattern of the highest calorie consumption on average compared to all other clusters, though not statistically significant [see Figure 4]. The trends observed in Cluster 4 across outcome variables suggest these children may be at the greatest risk for obesity which may suggest that being highly reinforced by food will lead to more food consumption and ultimately more weight gain, especially for those who are impulsive. Cluster 4 also displayed the best adherence to dietary recommendations [see Figure 5]. As with other clusters, this is likely due to the relationship between consumption (i.e., quantity) and HEI-2015 Total scores.

Although 4 distinct clusters were identified, we did not find any statistically significant differences between clusters for how closely nutritional guidelines were followed (HEI-2015 Total), the quantity of food consumed (kcal), or weight status (BMI z-score). This is likely due to the relatively small sample size, disproportionate cluster sizes, and skewed data. Despite lack of significant findings, there was a large effect (Cohen's *d*) between clusters 2 and 3 on HEI-2015 with cluster 3 having the larger mean. Cluster 3 includes children who were low impulsivity and highly reinforced by food compared to cluster 2 children who were high impulsivity and low on food reinforcement. Similarly, there was a large effect between clusters 3 and 4 on HEI-2015

with cluster 4 having the larger mean. Cluster 4 is comprised of children who are high impulsivity and highly reinforced by food. Regarding kcal consumption, Cohen's d analyses displayed large effects between clusters 1 and 4 and clusters 3 and 4 with cluster 4 demonstrating the larger mean. Cluster 1 includes children who are low impulsivity and low on food reinforcement. Future research may replicate this cluster analysis in a larger sample.

Limitations

The current study had several limitations. First, the data for DD and RRV_{food} were highly skewed. This limitation is likely due to measurement methods, and other research has reported similar skewness when using these measures among children (Best et al., 2012). Although the DD and RRV_{food} surveys were previously used with similar samples (Duckworth et al., 2010; Hill et al., 2009), they may not be efficacious enough to accurately capture these constructs. For instance, the items on the DD measure climb from days to weeks to months to a year. It is possible these quick changes in time are difficult for younger children in the study to fully grasp, leading to errors in reporting (Blything et al., 2015; Droit-Volet, 2013; Friedman, 1978). Likewise, the RRV_{food} measure contains hypothetical choice items that start at 20 clicks and escalate to 240 clicks. For the child's reference, researchers did have each child click a physical button 20 times; however, it is possible that younger children especially struggled with conceptualizing what it would take to click a button hundreds of times to achieve an award, leading to errors in responses. Relatedly, the sample size was relatively small and this likely impacted our capacity to detect statistical differences. A larger sample may have allowed for a more normal distribution due to having more observations across our variables of interest. It is possible our measures and low sample size do not capture the true variability within the assessed BE constructs. Second, we only collected data from one school which may have limited

generalizability. Third, the cross-sectional study design limits our ability to derive causal relationships between our variables of interest.

Future Directions

In order to understand and address pediatric obesity among diverse populations, food reinforcement and DD are important factors to consider. Although these are individual level variables, the approach to combatting pediatric obesity rates needs to incorporate system level factors. For example, more research on how environmental factors can buffer the relationship between DD, food reinforcement, and obesity is needed. Previous research has shown that neighborhood safety, access to playgrounds, and number of neighborhood grocery stores has been linked to obesity rates (Braveman & Gottlieb, 2014; Cummins & Macintyre, 2006; Gordon-Larsen et al., 2006). It is likely that an individual's level of food reinforcement and DD would have varying effects on their weight status when controlling for these environmental factors. In other words, if a child is highly reinforced by food, has high levels of DD and has access to playgrounds and other opportunities to engage in exercise, then the impact of these individual level variables on weight may be mitigated.

In addition to scaling intervention efforts up to incorporate individual and system level variables, more specific work should be done to better understand the role of DD and food reinforcement within diverse populations. Future studies should also work to acquire a larger sample of children from diverse backgrounds and re-assess the reinforcing pathology model of obesity considering: 1) Few BE model studies exist involving children from diverse backgrounds; 2) Replication is needed to see if the trends observed in the current study occur for similar samples and; 3) Due to skew and sample limitations, we were unable to accurately assess

the moderation model proposed by Best and colleagues (2012); therefore, a larger, more representative sample is needed for a direct evaluation of these relationships.

Finally, although the term is widely used, “reinforcing pathology model” is potentially stigmatizing and inappropriate. Given that our study was conducted among children who have been systemically oppressed, “choices” regarding healthful foods are often limited making it difficult to determine what is actually “choice” as opposed to limited options and certainly does not imply pathology. A pathology-focused model may unintentionally place blame on individuals who are limited by the options they have available. As mentioned previously, the school meal program aims to reduce food insecurity by providing healthful foods to all children. However, not all children have access to the school meal program and not all children have access to healthful foods at home. Thus, the pathology-focused label is not appropriate. Further, the word “pathology” implies a specific disease or disorder; however, the model is not related to a specific condition or diagnosing a condition. Finally, pathology implies a dichotomous outcome. Our findings point to clusters that illustrate a dimensional risk with some individuals being at greater risk of developing obesity compared to others. The model should be named to highlight this “spectrum of risk” depending on how someone rates on reinforcement of food and impulsivity. Therefore, re-naming the model “The reinforcement-impulsivity risk model” would allow the interaction of the variables to be highlighted while underscoring the model’s ability to measure the *risk* of developing whichever disorder is being studied (i.e., obesity or drug use). The current study is the first to utilize a person-centered approach investigating connections between DD, RRV_{food} , and weight status among children from minority backgrounds. These findings spur hypothesis generation and provide the groundwork necessary for full scale hypothesis testing of the reinforcing pathology model in a larger sample of marginalized youth,

which may inform the development of tailored interventions to combat pediatric obesity in the future.

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Table 1. Sample Demographics (*n* = 88)

	<i>M</i> (<i>SD</i>)
Age	8.1 (1.2)
Height (cm)	129.5 (9.4)
Weight (lbs)	72.3 (24.3)
DD	6.02 (2.49)
RRV_{food}	4.10 (4.72)
BMI z-Score	0.88 (1.17)
Total Calories	350.41 (173.75)
Total HEI-2015	55.00 (10.47)
	<i>%</i> (<i>n</i>)
Sex	
Male	48.9 (43)
Female	51.1 (45)
Grade	
First	31.8 (28)
Second	27.3 (24)
Third	17.1 (15)
Fourth	23.9 (21)
Race/Ethnicity	
Hispanic	77.3 (68)
Black	10.2 (9)
Other	12.5 (11)
BMI Category	
Underweight	3.4 (3)
Normal	45.5 (40)
Overweight	22.7 (20)
Obese	27.3 (24)

DD – Delay Discount;

RRV_{food} – Relative Reinforcing Value of Food;

BMI z – Standardized Body Mass Index score;

HEI – Healthy Eating Index

Table 2. Means and Standard Deviations across Clusters

Cluster	DD		RRV		kcal		HEI-2015		zBMI	
	<i>M</i>	<i>(SD)</i>	<i>M</i>	<i>(SD)</i>	<i>M</i>	<i>(SD)</i>	<i>M</i>	<i>(SD)</i>	<i>M</i>	<i>(SD)</i>
1. Low DD, Low RRV (<i>n</i> =45)	5.06	(2.37)	2.22	(1.28)	335.50	(161.12)	54.43	(11.31)	0.80	(1.13)
2. High DD, Low RRV (<i>n</i> =22)	8.00	(0.00)	1.41	(1.05)	350.25	(184.40)	57.14	(8.79)	0.98	(1.31)
3. Low DD, High RRV (<i>n</i> =11)	4.88	(2.95)	11.36	(5.39)	314.93	(136.10)	50.22	(8.05)	0.84	(1.45)
4. High DD, High RRV (<i>n</i> =9)	8.00	(0.00)	11.22	(4.71)	438.45	(233.25)	59.17	(11.27)	1.03	(0.76)

DD – Delay Discount; RRV_{food} – Relative Reinforcing Value of Food; kcal – calories; zBMI – Standardized Body Mass Index score

Table 3. Correlations

	RRV _{food}	DD	HEI-2015 Total	kcal	BMI Z-score	Height (cm)	Weight (lbs)	Age (years)	Sex (0=F;1=M)	1st Grade	2nd Grade	3rd Grade	4th Grade	Latinx/ Hispanic	Black	Other
1	-															
2	-.011	-														
3	-.158	.036	-													
4	.040	.039	.268*	-												
5	.074	.015	.007	.168	-											
6	-.037	.097	-.136	-.026	.180	-										
7	-.035	.084	-.111	.127	.690**	.713**	-									
8	-.120	.002	-.073	-.047	-.021	.729**	.402**	-								
9	.096	.018	-.153	.283*	-.031	.179	.088	.234*	-							
10	.105	-.082	.112	.073	-.024	-.597**	-.305**	-.800**	-.033	-						
11	.063	.180	-.135	.056	.123	-.113	-.081	-.135	-.292**	-.418**	-					
12	-.140	.057	.136	-.217	-.044	.241*	.116	.336*	.222*	-.310**	-.278**	-				
13	-.059	-.149	-.099	.054	-.062	.557**	.313**	.719**	.146	-.382**	-.343**	-.254*	-			
14	.059	-.020	.138	-.035	-.051	-.253*	-.158	-.065	.042	.196	-.216*	-.115	.113	-		
15	-.040	.052	.009	.102	.034	.168	.177	-.001	-.030	-.070	.130	.046	-.101	-.622**	-	
16	-.038	-.022	-.183	-.049	.034	.167	.043	.083	-.026	-.184	.154	.103	-.050	-.697**	-.128	-

DD – Delay Discount; RRV_{food} – Relative Reinforcing Value of Food; kcal – calories; zBMI – Standardized Body Mass Index score

* = $p < .05$; ** = $p < .01$; *** = $p < .001$

Table 4. Cluster ANOVA Comparisons

	<i>n</i>	<i>M</i> (<i>SD</i>)	<i>F</i>	<i>p</i>
<i>Comparison 1: HEI-2015</i>				
1. LowDDLowRRV	39	54.43 (11.31)	1.556	0.207
2. HighDDLowRRV	22	57.14 (8.79)		
3. LowDDHighRRV	10	50.22 (8.05)		
4. HighDDHighRRV	9	59.17 (11.27)		
<i>Comparison 2: kcal</i>				
1. LowDDLowRRV	39	335.50 (161.12)	0.999	0.398
2. HighDDLowRRV	22	350.25 (184.40)		
3. LowDDHighRRV	10	314.93 (136.08)		
4. HighDDHighRRV	9	438.45 (233.25)		
<i>Comparison 3: zBMI</i>				
1. LowDDLowRRV	45	.80 (1.13)	0.156	0.925
2. HighDDLowRRV	22	.98 (1.31)		
3. LowDDHighRRV	11	.84 (1.45)		
4. HighDDHighRRV	8	1.03 (0.76)		

DD – Delay Discount; RRV_{food} – Relative Reinforcing Value of Food; kcal – calories; zBMI – Standardized Body Mass Index score; HEI – Healthy Eating Index

Table 5. Effect Sizes (Cohen's *d*) and their Confidence Intervals between Clusters on HEI-2015

HEI-2015	Cohen's <i>d</i>	95% CI
C1C2	-0.2585	-0.7831 - 0.2661
C1C3	0.3912	-0.3079 - 1.0902
C1C4	-0.4194	-1.1490 - 0.3103
C2C3	0.8070	0.0338 - 1.5802
C2C4	-0.2128	-0.9901 - 0.5645
C3C4	-0.9227	-1.8699 - 0.0244

C1 = Cluster 1 (LowDDL_{LowRRV}); C2 = Cluster 2 (HighDDL_{LowRRV});

C3 = Cluster 3 (LowDDHighRRV); C4 = Cluster 4 (HighDDHighRRV)

Cohen's *d*: 0.2 - *small* effect size, 0.5 *medium* effect size, 0.8 *large* effect size

Table 6. Effect Sizes (Cohen's *d*) and their Confidence Intervals between Clusters on kcal

kcal	Cohen's <i>d</i>	95% CI
C1C2	-0.0869	-0.6097 - 0.4359
C1C3	0.1313	-0.5639 - 0.8265
C1C4	-0.5856	-1.3198 - 0.1486
C2C3	0.2061	-0.5431 - 0.9553
C2C4	-0.4430	-1.2264 - 0.3403
C3C4	-0.6564	-1.5809 - 0.2680

C1 = Cluster 1 (LowDDL_{LowRRV}); C2 = Cluster 2 (HighDDL_{LowRRV});

C3 = Cluster 3 (LowDDHighRRV); C4 = Cluster 4 (HighDDHighRRV)

Cohen's *d*: 0.2 - *small* effect size, 0.5 *medium* effect size, 0.8 *large* effect size

Table 7. Effect Sizes (Cohen's *d*) and their Confidence Intervals between Clusters on zBMI

zBMI	Cohen's <i>d</i>	95% CI
C1C2	-0.1511	-0.6616 - 0.3594
C1C3	-0.0335	-0.6927 - 0.6258
C1C4	-0.2116	-0.9648 - 0.5415
C2C3	0.1032	-0.6210 - 0.8274
C2C4	-0.0418	-0.8511 - 0.7675
C3C4	-0.1565	-1.0685 - 0.7556

C1 = Cluster 1 (LowDDL_{Low}RRV); C2 = Cluster 2 (HighDDL_{Low}RRV);

C3 = Cluster 3 (LowDDHighRRV); C4 = Cluster 4 (HighDDHighRRV)

Cohen's *d*: 0.2 - *small* effect size, 0.5 *medium* effect size, 0.8 *large* effect size

Figure 1. Dendrogram using Ward Linkage



Figure 2. Histogram of Delay Discount Variable

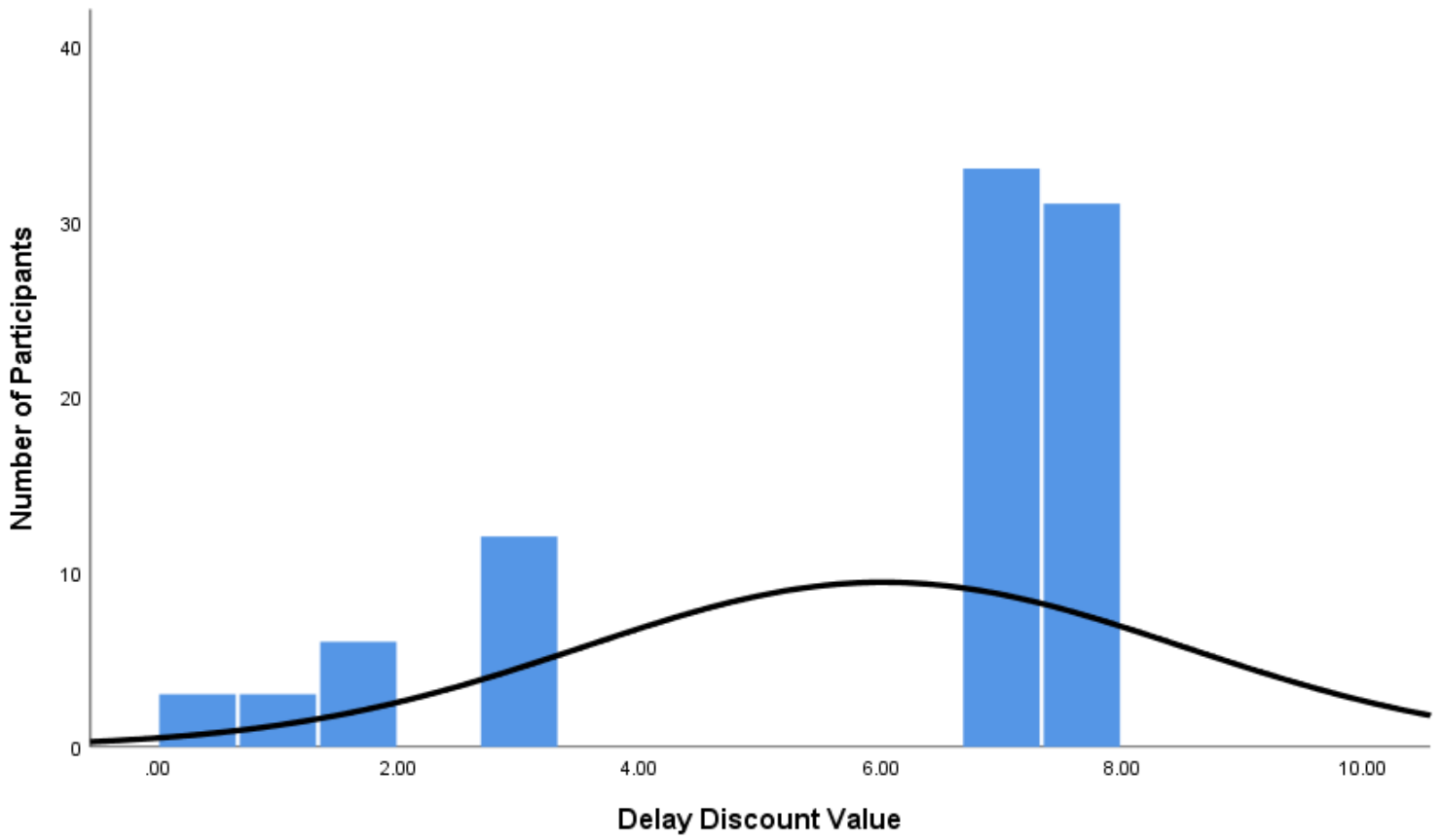


Figure 3. Average BMI z-Score Across Clusters

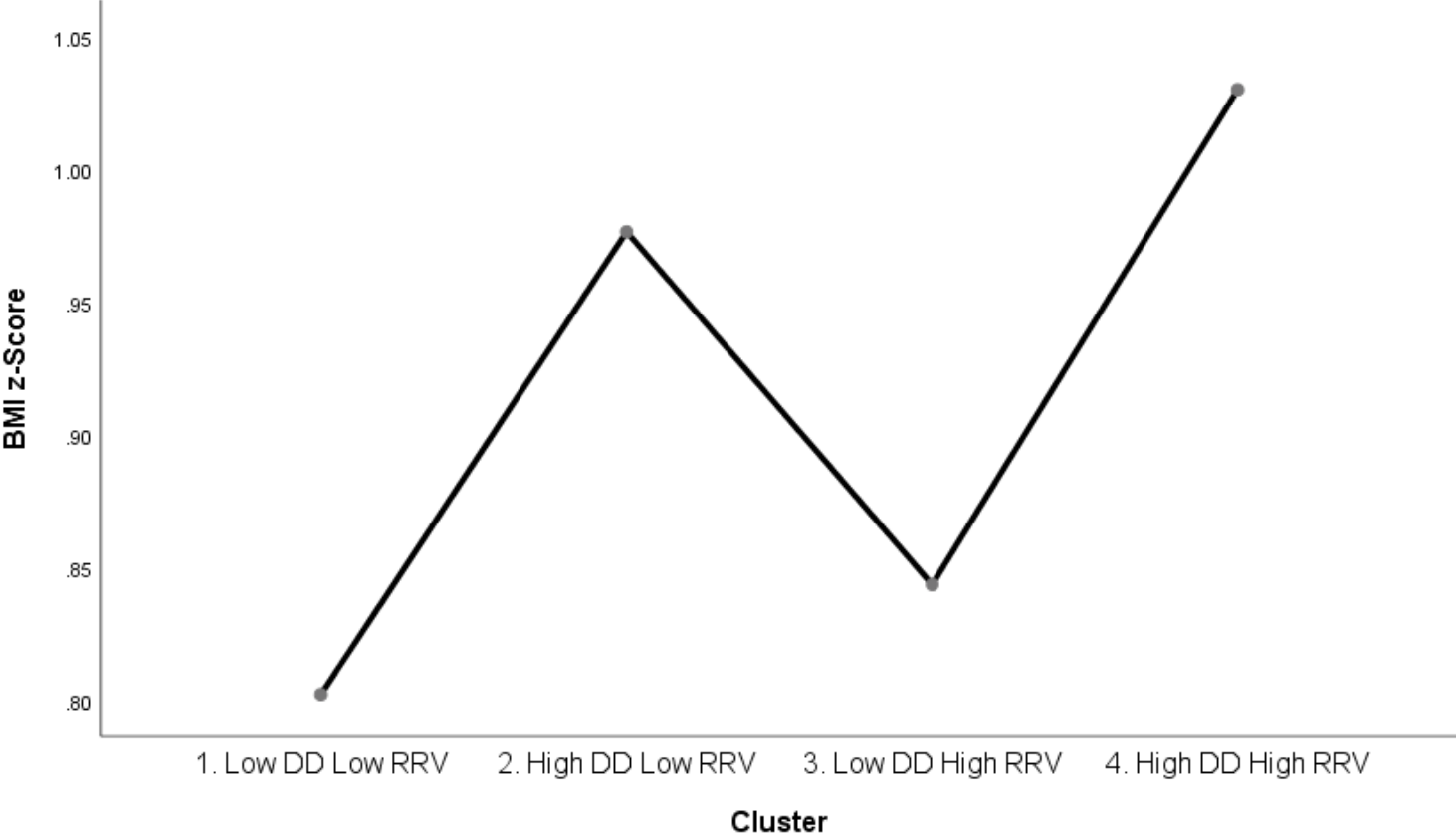


Figure 4. Average kcal Vlaue Across Clusters

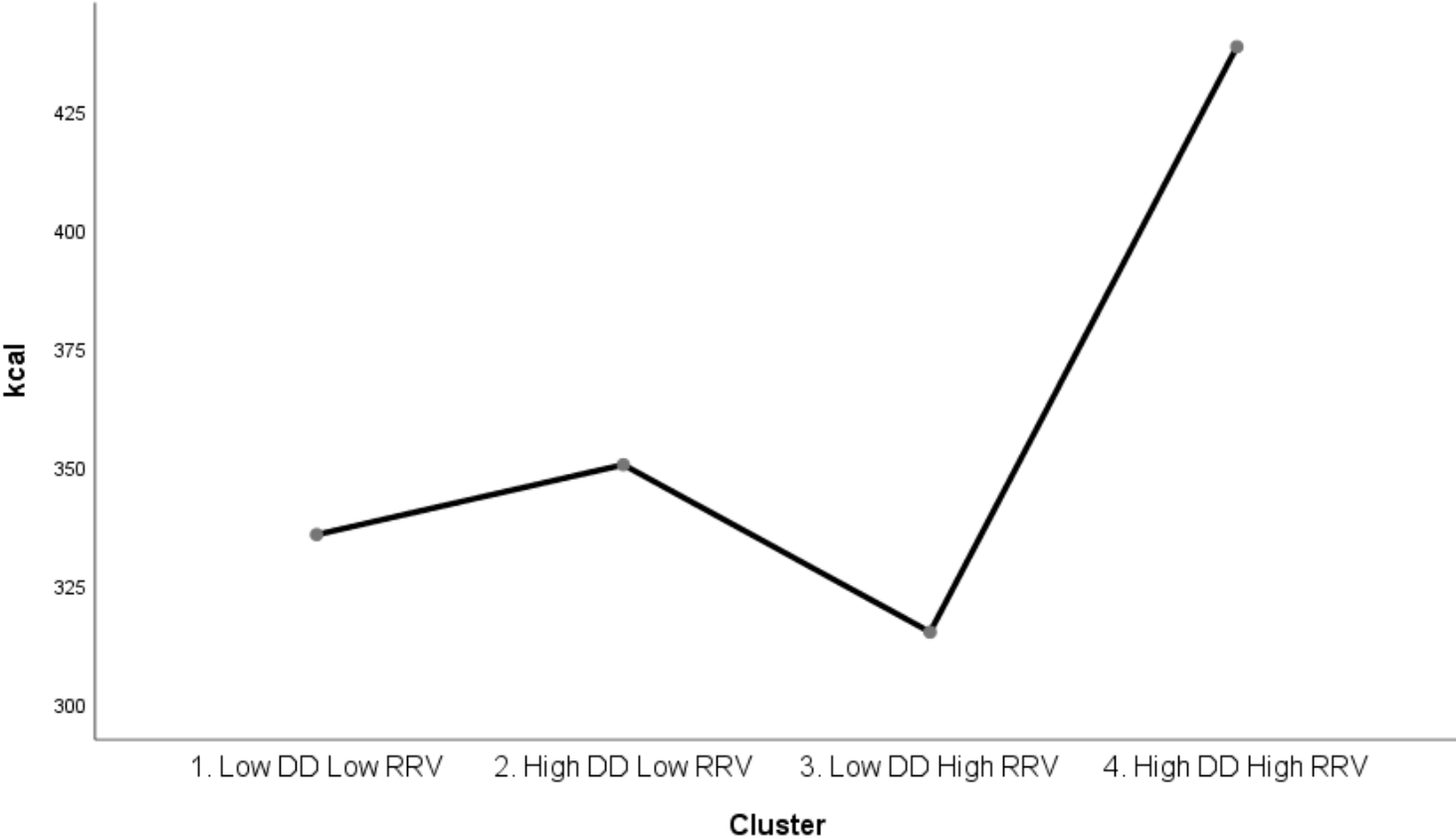
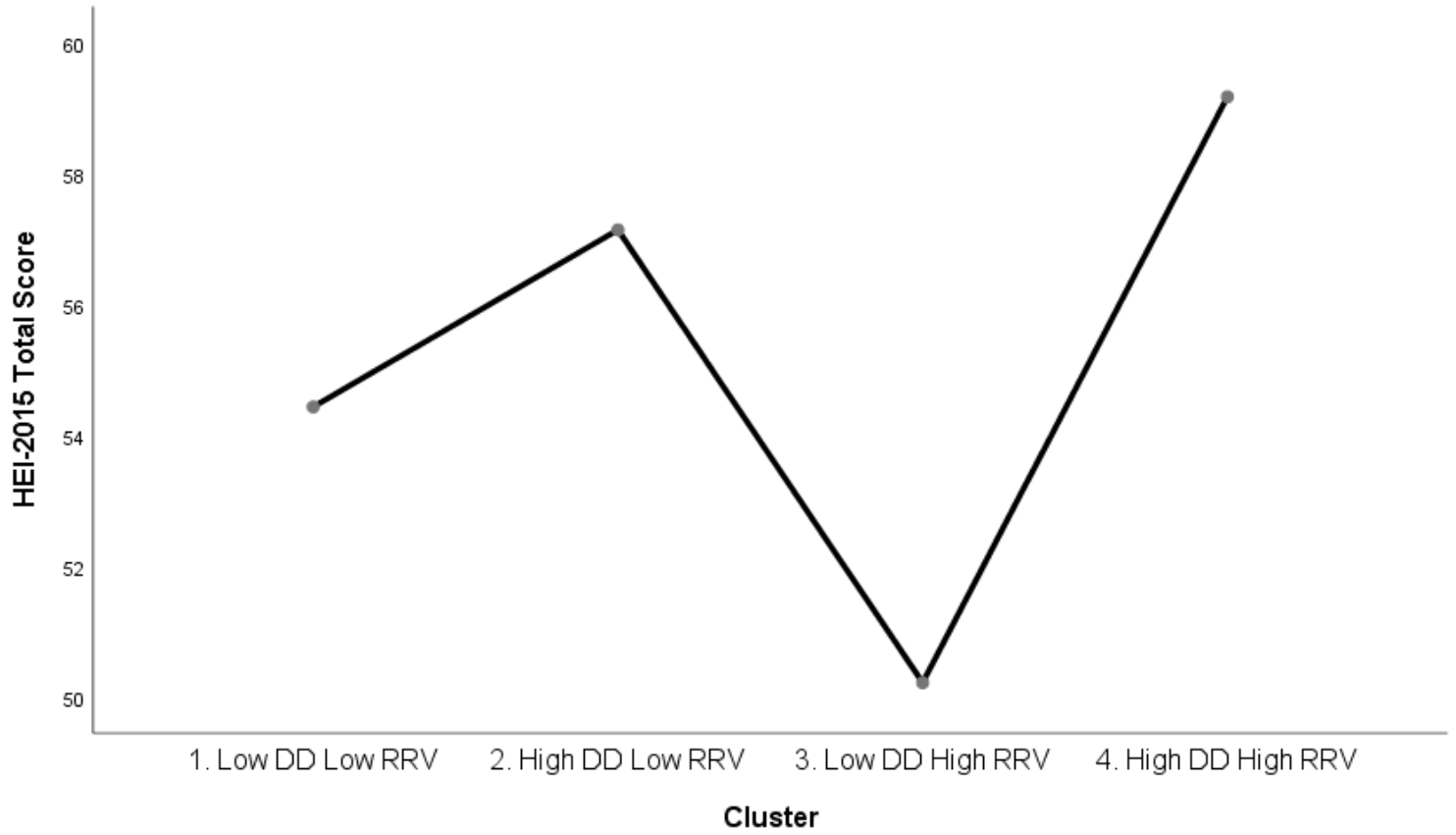


Figure 5. Average Diet Quality Value Across Clusters



Appendix A: Original Thesis Proposal

Dietary Intake and Body Mass Index among Marginalized Youth: Assessing the Reinforcing
Pathology Model of Obesity

Proposal for a Thesis

Presented to

The Department of Psychology

DePaul University

By

Bernardo Loiacono

Table of Contents

Abstract.....3

Introduction.....4

 Pediatric Obesity.....4

 Diet Quality.....5

 Behavioral Economic Theory.....6

 Relative Reinforcing Value of Food6

 Delay Discounting.....8

 The Reinforcing Pathology Model.....9

 Rationale.....12

Method.....13

 Participants.....13

 Design.....14

 Recruitment.....14

 Procedure.....14

Measures.....15

 Computer Task.....15

 Delay Discounting.....15

 Relative Reinforcing Value of Food.....16

 Diet Quality.....17

 Food Consumption.....18

 Child BMI z-score.....18

Analytic Design and Statistical Analysis.....18

References.....21

Appendices.....28

Abstract

Obesity among children within the United States of America continues to be national health concern. Specifically, obesity and higher weight statuses have been linked to various poor physical (i.e. musculoskeletal discomfort, asthma, etc.) and psychological (i.e. depression, low self-esteem, etc.) health outcomes. This link is especially salient for children belonging to minority groups since they are disproportionately impacted by obesity. Diet quality and consumption behaviors have been shown to be one of the most influential factors in predicting weight status and gain. Therefore, understanding what factors influence consumption behaviors among minority youth is important. Since consumption and diet quality involve choice, Behavioral Economics (BE) has provided a theoretical framework for understanding what social, psychological, and cultural factors impact decision making regarding food consumption. BE in the obesity literature has identified poor executive control (i.e. impulsivity) and relative value of food (RRV_{food}) as two main behavioral components that predict consumption habits. The reinforcing pathology model, sometimes referred to as the reinforcer pathology model or reinforcement pathology model has been used successfully to describe drug and alcohol addiction such that the relation between reinforcement and use is moderated by impulsivity. Some have suggested that eating behaviors and obesity may operate the same way. The current project aims to assess the reinforcing pathology model of eating and obesity among a diverse sample of children in 1st to 4th grade. To our knowledge, this will be the first study to test the reinforcing pathology model among a younger, predominantly non-white sample within a school setting.

Dietary Intake and Body Mass Index among Marginalized Youth: Assessing the Reinforcing
Pathology Model of Obesity

Pediatric Obesity

The prevalence of childhood obesity in the United States of America is 18.5%, with obesity disproportionately impacting low-income and minority youth (25.8% among Hispanic children and 22% among Black children compared to 14.1% among non-Hispanic White children) (National Center for Health Statistics, 2017). In addition, the prevalence of pediatric obesity increases with age: 13.9% of two to five-year-olds, 18.4% of six to 11-year-olds, and 20.6% of 12- to 19-year-olds are currently obese in the United States (National Center for Health Statistics, 2017). These trends are salient since obesity has been associated with the development of numerous chronic health conditions such as cardiovascular disease, various cancers, diabetes, asthma and sleep apnea, musculoskeletal discomfort, depression, anxiety, and low self-esteem (Center for Disease Control and Prevention, 2018). The link between obesity and these diseases are significant because each year, heart disease (635,260 deaths), cancer (598,038 deaths), and diabetes (80,058 deaths) comprise the first, second, and seventh leading causes of death, respectively, in the United States (National Center for Health Statistics, 2018). The need to understand and combat obesity in childhood is of great importance since obesity in early life is associated with increased risk of obesity in adulthood (Gordon Larsen, The, & Adair, 2010; Parsons, Power, Logan, & Summerbelt, 1999). Notably, obesity is a complex issue and its contributing factors have been especially difficult to understand among minority youth since the inclusion, and retention, of individuals of low-income and minority status in research continues to be a problem (Nicholson et al., 2011).

Diet Quality

Extensive research has been conducted to determine which factors contribute to childhood obesity. Currently, the CDC (2018) recognizes multiple contributing factors including genetics, diet, community characteristics, sleep patterns, and level of physical activity. Among these predictors, diet has been shown to be one of the most influential regarding weight gain (Hu et al., 2016; Jennings, Welch, van Sluijs, Griffin, & Cassidy, 2011; Niemeier, Raynor, Lloyd-Richardson, Rogers, & Wing, 2006; Sahoo et al., 2015). Over time, individuals become at risk for obesity when their energy intake exceeds their expenditure. Therefore, consumption and dietary habits are important considerations when understanding excessive weight gain in children. Diet quality refers to how well an individual's diet matches the national nutritional guidelines published by the US Department of Agriculture (USDA) and Health and Human Services (HHS) (DeSalvo, Olson, & Casavale, 2016; Guenther et al., 2013). Consumption of energy dense foods, such as foods containing high amounts of fats and sugars, are important given their link to obesity and other health problems (Pérez-Escamilla, 2012). In a recent review looking at the causes and consequences of childhood obesity, Sahoo and colleagues (2015) stated that diets that include large portions of fast food, sugary beverages, and snack foods have been associated with weight gain. These foods tend to contain low nutritional value but contribute to excessive caloric intake when consumed. This is especially true for common sugary drinks (i.e. soda, juice, sweet tea, and other sweetened beverages) because they can be consumed very quickly and are less filling compared to food consumption (Sahoo et al., 2015). Finally, dietary modifications tend to be incorporated into weight loss programs for children due to diet's relationship to weight status (Snethen, Broome, & Cashin, 2006). Therefore, by understanding what drives unhealthy eating behavior, we are better prepared to develop effective and

sustainable obesity prevention and treatment interventions. Although food overconsumption can be explained by internal factors (hunger, experience with food, mood, glucose/insulin levels) and external factors (price and appearance of food, time of day, social contexts), the reinforcing value of food has been shown to be an important factor in overeating (Temple, 2014).

Behavioral Economic Theory

Behavioral economic (BE) theory has been used to operationalize the reinforcing value of food (Best et al., 2012). Broadly, BE is the study of how psychological and cognitive states and cultural and social factors influence decision making among individuals (Camerer & Loewenstein, 2003). According to BE theory, addiction is often conceptualized as pathological patterns of behavior to stimuli and reinforcers (Bickel et al., 2011). These pathological patterns include level of reinforcement and level of impulsivity to a specific stimulus (i.e. drug, alcohol, food, etc.).

Relative Reinforcing Value of Food

From a BE perspective, reinforcing value has been conceptualized as how much work an individual is willing to engage in to acquire a reward when given alternatives (Epstein et al., 2018; Epstein, Leddy, Temple, & Faith, 2007). This measure of reinforcement assumes that the more value someone puts on a reward, the harder they will work for it. Temple (2014) has reviewed several factors that influence level of food reinforcement. These factors included level of hunger, weight status, and type of food. Foods that contain large amounts of fats and sugars (i.e. cookies, chips, sweetened beverages, etc.) tend to be more reinforcing compared to more nutritious foods (i.e. fruits and vegetables). Because energy dense foods are highly palatable, encouraging individuals to choose healthier alternatives can be difficult, especially for individuals who are obese (Temple, 2014). The reinforcement of food for individuals who are

obese has been likened to reinforcement of drugs for individuals who have drug use disorders (Temple, 2016; Carr, Daniel, Lin, Epstein, 2011).

Reinforcement within the BE eating behavior literature is often operationalized as the relative reinforcing value of food (RRV_{food}). RRV_{food} is typically measured via a behavioral task that involves making a choice between two reinforcers (e.g., an energy dense food (i.e. a cookie) vs. a non-food substitute (i.e. a sticker)) (Goldfield, Epstein, L. H., Davidson, & Saad, 2005). To receive the reinforcer, participants are asked to determine a “behavioral cost” in the form of work (i.e. certain number of button clicks) (Epstein, Salvy, Carr, Dearing, & Bickel, 2010) or hypothetical purchase tasks (Epstein et al., 2018). Choosing to work, or pay, more for a food reinforcer (e.g., more button clicks) indicates that the individual is reinforced to a greater extent by food compared to an alternative.

Research has shown that children with obesity tend to have higher levels of RRV_{food} than their normal weight peers (Best et al., 2012). This relationship between RRV_{food} and weight has been shown in children as young as three to five years old (Rollins, Loken, Savage, & Birch, 2014). Specifically, children with higher BMI z-scores worked harder (i.e. clicked the button faster) to acquire food compared to children with lower BMI z-score values. Research on RRV_{food} and obesity has also found overweight children ages 8 to 12 to be consistently more reinforced by food compared to their non-overweight counterparts (Temple, Legierski, Giacomelli, Salvy, & Epstein, 2008). Specifically, children who were overweight found food more reinforcing compared to non-food alternatives (i.e., handheld video games, word searches, or magazines) and had higher rates of energy consumption; additionally, energy intake and BMI z-scores were highly correlated with RRV_{food} scores. Longitudinally, among children ages seven to ten, RRV_{food} scores at baseline predicted increases in BMI and fat mass index at a one-year

follow up (Hill, Saxton, Webber, Blundell, & Wardle, 2009). RRV_{food} has also been predictive of short-term calorie and gram consumption in a sample of women (Brace & Yeomans, 2015). In sum, there appears to be a link between reinforcement and actual energy intake. However, little literature exists looking at RRV_{food} among young, diverse samples in the school setting that use objective evaluations of diet and food consumption.

Delay Discounting

According to BE theory, in addition to RRV_{food} , individuals who are highly reinforced by food tend to also be more impulsive and discount the value of larger future rewards (Epstein, Dearing, Temple, & Cavanaugh, 2008; Stojek, & MacKillop, 2017). Although the construct of impulsivity can be multifaceted (Leshem & Glicksohn, 2007; Parker, Bagby, & Webster, 1993), impulsivity as it pertains to BE focuses on the ability to delay immediate gratification of smaller rewards for later, larger rewards. To measure this specific aspect of impulsivity, called delay discounting (DD), children are asked if they would prefer a smaller immediate food reward to a later, more sizable food reward. A child who is unable to delay for larger rewards would be identified as more impulsive (Mischel & Metzner, 1962).

Research on DD has suggested that young children (age 4) who have difficulty delaying rewards are 1.3 times more likely to be overweight in late childhood or early adolescence (Seeyave et al., 2009). A large U.S. cohort study that tracked child weight gain from ages 3 to 12 also supports this trend (Francis & Susman, 2009). Specifically, children who scored low on DD and self-regulation measures in early childhood gained the most weight throughout the study. These findings suggest that high impulsivity in early childhood may be a risk factor contributing to the development of obesity in adolescence. Studies on DD and child body mass index (BMI) have also found that children and adolescents who were better at delaying rewards tended to

have lower BMI scores, and were able to lose weight easier, compared to youth who had higher DD scores (Duckwortha, Tsukayamaa, & Geier, 2010; Epstein, Salvy, Carr, Dearing, & Bickel, 2010; Best et al., 2012; Fields, Sabet, & Reynolds, 2013; Stojeka & MacKillop, 2017). Fifth graders who demonstrated lower impulsivity had lower BMI z-scores in 8th grade, suggesting that lower levels of impulsivity was a protective factor against excessive weight gain (Duckwortha, Tsukayamaa, & Geierb, 2010). Overall, a recent meta-analysis on DD methods (measures using food and monetary rewards) has found steep discounting to be a consistent feature of individuals experiencing obesity (Amlung, Petker, Jackson, Balodis, & MacKillop, 2016). Similar to RRV_{food} , little literature exists on DD among minority youth samples with an objective measure of diet quality and consumption within the school setting.

The Reinforcing Pathology Model

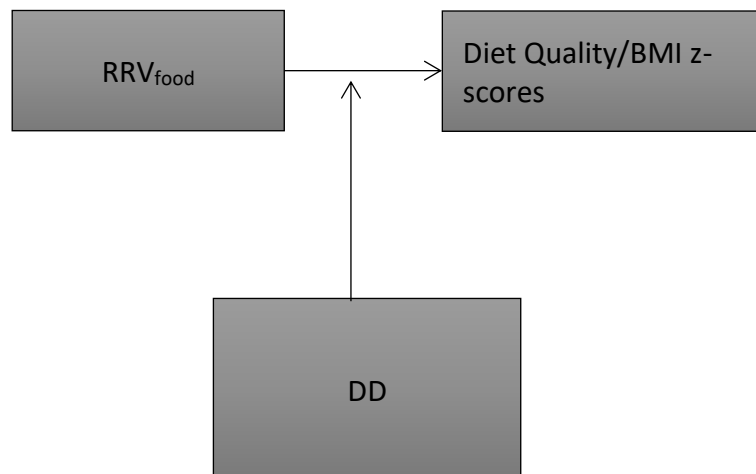
BE theory research in the area of obesity has identified RRV_{food} and DD as a way to measure the main components of the reinforcing pathology model, sometimes referred to as the reinforcer pathology model or reinforcement pathology model (Bickel, Johnson, Koffarnus, MacKillop, & Murphy, 2014; Francis & Susman, 2009; Temple et al., 2008). The reinforcing pathology model was originally used to understand drug and alcohol addiction (Bickel et al., 2014). However, some have suggested parallels between overeating and drug addiction (Temple, 2016; Carr, Daniel, Lin, Epstein, 2011). The reinforcing pathology model suggests that there is an interaction between an individual's motivation and executive function processes that can lead to overeating. Specifically, energy dense foods have been shown to be significantly more rewarding for individuals who are obese compared to their non-obese counterparts (Temple et al., 2008). This reinforcement can lead to an increase motivation to pursue highly palatable foods over other alternatives. The reinforcing value of food in this context can be similar to the

reinforcing properties of drugs for a frequent user. Specifically, research has shown that repeated exposure to high fat/sugary foods increases sensitization for obese individuals but not other adults (Temple, 2016). Increased sensitization builds tolerance and requires an individual to consume more of a stimulus or reward to achieve similar effects (i.e. satiation). Similarly, sensitization increases the likelihood of withdrawal when the preferred stimulus is absent or consumed to a lesser degree. Sensitization to foods is one reason diets that require an individual to refrain from consuming any junk food are difficult to sustain overtime (Temple, 2016). Temple (2016) has also suggested that the process of sensitization to energy dense foods for obese adults is predictive of weight gain.

In addition to reinforcement, the reinforcing pathology model focuses on executive functioning and an individual's ability to self-regulate. The model states that higher levels of impulsivity will strengthen the relationship between reinforcement and consumption. This concept is noteworthy given that individuals who are obese tend to display higher levels of impulsivity compared to their leaner counterparts (Amlung et al., 2016; Bickel, 2014). This finding suggests that cognitive control over eating behavior may be more difficult for individuals who are of a higher weight status. Specifically, individuals who are obese may choose to consume rewarding food immediately even when given an option for a greater food reward at a later time. In combination, those who are highly reinforced by unhealthy food, and have difficulty delaying rewards, are predicted to be at greatest risk of overconsumption and obesity. According to a systematic review by Giel, Teufel, Junne, Zipfel, and Schag (2017), this pattern of food-specific sensitivity and impaired inhibitory control is increased for individuals who are obese and especially prominent for those experiencing Binge Eating Disorder. This suggests that impulsivity and food reinforcement may be important components to target in the context of

obesity treatment and prevention interventions. The reinforcing pathology model has also been well understood in samples of overweight and obese women, and findings have shown that this “neurobehavioral model” to be strongly related to weight status and palatable food intake (Appelhans et al., 2011). However, the authors are unaware of any study aimed at understanding this model among younger children, from low-income and minority backgrounds, within a non-laboratory setting. This population is especially important given their high-risk for developing obesity.

Specific BE findings on the reinforcing pathology model and obesity suggests that DD might moderate the relationship between RRV_{food} and weight status (see figure 1), but notes that more research on the coupled effects of DD and RRV_{food} among overweight children is needed (Best et al., 2012). Likewise, it has been previously mentioned that the relationship between food reinforcement and ability to delay gratification “may be the behavioral phenotype that may be most associated with high energy intake” (Epstein, Salvy, Carr, Dearing, & Bickel, 2010). Simply, the reinforcing model may be the best behavioral description of why certain individuals experience difficulty with moderating their food intake and overconsume food. Despite this abundant research on DD and RRV_{food} , much of it has been conducted among children seven and older and White children from higher socioeconomic backgrounds (Staubitz, Lloyd, & Reed, 2018).



Rationale

Much of the existing literature describes research that utilize labs to conduct their studies rather than real world settings. This limitation is important to note considering children are seldom in these controlled settings when making choices around food. Therefore, more research is needed in children's natural settings where food consumption is most common. Specifically, factors that influence children's eating habits, behaviors, and intake at school are especially important. A recent large national survey study in America indicated that, for children who consume breakfast and lunch at school, children receive almost half (47%) of the day's energy intake at school: 41% of daily vegetables, 58% of daily fruit, 52% of daily grains, and 77% of daily milk/dairy (Cullen & Chen, 2017). Consequently, school is an important environment regarding children's food consumption and nutritional quality. Within the lunchroom setting, children are often given choice over what to eat. Therefore, understanding how children make choices, and what factors influence food selection and consumption, is worth exploring in order to encourage healthy food consumption and reduce the risk of obesity in adulthood. Although previous research has explored both DD and RRV_{food} , no studies to date have tested the reinforcing pathology model among underserved elementary school children.

The main purpose of the current study is to:

- 3) Determine the relationship between RRV_{food} , DD, and diet quality/BMI z-score among a non-white sample

Hypothesis I: RRV_{food} will be a significant predictor of child BMI z-score, diet quality, and calorie intake

Hypothesis II: DD will be a significant predictor of child BMI z-score, diet quality, and calorie intake

- 4) Test the reinforcing pathology model of obesity by determining whether DD moderates the relationship between RRV_{food} and diet quality/BMI z-score among a diverse sample of low-income 1-4th graders. Outcome variables will include diet quality, BMI z-score, and calorie consumption (kcal) while in the school setting.

Hypothesis III: Higher RRV_{food} scores will predict higher calorie intake, lower diet quality, and higher BMI z-scores, but especially for children with steeper DD scores.

These findings will help inform our understanding of the relationship between motivation (reinforcement) and executive functioning (impulsivity) among marginalized, urban minority youth. Further, this study will address an important gap in the literature given that these children are disproportionately affected by obesity but are often underrepresented in pediatric obesity studies in this area.

Method

Participants

Participants consisted of primary school aged children in grades 1st through 4th in Chicago, Illinois. In total, 88 students (28 -1st graders, 24 - 2nd graders, 15 - 3rd graders, and 21 - 4th graders) participated. Demographically, this student sample was 51.1% female with large percentages of racial minorities: 77.3% Hispanic, 10.2% African-American, and 12.5% Other. Parents received a \$25 Amazon gift card for their child's participation.

Design

This study implemented a cross-sectional design . For Hypotheses I and II, separate models will be tested with two separate predictor variables, relative reinforcing value of food and DD, and three criterion variables, BMI z-score, diet quality, and caloric consumption. Delay discounting will also be explored as a moderating variable of relations between RRV_{food} and outcome variables in separate models.

Recruitment

Three strategies were utilized for recruitment. 1) Informative folders containing flyers and blank consent forms were sent home with all children so that parents could be informed of the study and its purposes, 2) research assistants attended school orientation day and passed out information folders to interested parents directly, and 3) research assistants were present for report card pick-up day to distribute information folders to parents not yet enrolled. The informative flyers explained our interest in understanding children's food preferences, food consumption in school (i.e. type of food and amount consumed), and behavior (i.e. RRV_{food} , DD, etc.). Interested parents returned signed consent forms to their child's school that were later collected by a research assistant.

Procedure

Children who received parent permission participated in the study during their elective classes (music, dance, gym, technology). Prior to participation, children were also asked to provide assent. Following the assent process, trained research assistants (RA) administered the delay discounting (DD) and Relative Reinforcing Value of Food (RRV_{food}) tasks with the children. Each measure was administered on a laptop computer. Anthropometric data was also collected using a stadiometer to measure height (cm) and a scale to measure weight (lb). After

surveys and anthropometric data were completed, the research team returned to the school to measure lunchroom food consumption. Data on lunchroom food consumption occurred over two days: DATE (grades) and DATE (grades). On these days, teachers were given a list containing the names of their students who were enrolled in the study and asked to place these children at the front of the line when bringing their class down for lunch. Upon entering the lunchroom, a RA recorded the child's ID on their paper lunch tray with a food safe marker. After the children selected their food, another RA captured a photo of the lunch tray at the end of the line. Children were instructed to raise their hand once they were finished with their lunch. Once a child raised their hand, photos of the child's post-consumption plate were taken by RAs.

Measures

Computer Task.

The computer task began by having children rank order their favorite foods from a list of unhealthy and healthy options that were typically served in the school lunchroom. This list contained common foods (i.e. apples, candy, oranges, cookies, ice cream, celery, etc.). The highest ranked unhealthy and healthy foods were used for the DD and RRV_{food} tasks. Using children's top ranked foods for these measures ensures responses were not influenced by preference (i.e. if cookies were used for all children, then children who like cookies may respond differently than children who do not like cookies on these measures).

Delayed Discounting (DD; Appendix A).

The DD task consisted of 9 items that asked the child to pick between an immediate food reward and a delayed food reward (Mischel & Metzner, 1962). The food reward was the food item that was ranked highest by the child. The image of the selected food was shown for each item to help children understand the questions. An example item would be, "Would you rather

have one slice of pizza today or two tomorrow?” One pizza slice appeared for the immediate reward option (now) and two slices appeared next to the delayed reward (tomorrow). The delay increased with each item, but the immediate reward is held constant at “today”: one today – two today, one today – two tomorrow, one today – two in five days, one today – two in one week, etc. RAs read each item to all participants and responses were selected (clicked) by the child or the RA, depending on child preference. Steeper delay discount scores indicate higher levels of impulsivity (Best et al., 2012). Best and colleagues (2012) found that food DD tasks displayed convergent validity with monetary DD tasks. Likewise, a meta-analysis looking at various self-control measures has suggested that there is acceptable convergent validity between DD tasks and other impulsivity measures (Duckworth & Kern, 2011).

Relative Reinforcing Value of Food (RRV_{food}; Appendix B).

RRV_{food} consisted of 12 items and assesses the reinforcing value of energy dense food (Goldfield, Epstein, L. H., Davidson, & Saad, 2005). These items appeared as a list of comparisons between the child’s highest ranked unhealthy food and highest ranked unhealthy food. For this task, children were asked if they would prefer to click a button (work) a certain number of times for the unhealthy food or healthy food. The number of clicks are held constant for the healthy food but increase in a fixed interval for the unhealthy food item with each question. The point at which the child no longer prefers to click the button for the unhealthy food, two items in a row, indicates a switch point and the reinforcing value of the unhealthy food. Example items include 20 button presses for a cookie - 20 for an apple, 40 button presses for a cookie – 20 for an apple, 60 button presses for a cookie – 20 for an apple, etc. These items were read by RAs as hypothetical scenarios. Children were asked to press a physical button 20 times to provide perspective for items asking if they would press the button more times for later

items. Hypothetical RRV_{food} button press tasks have been validated among adults (Goldfield et al., 2005) and has been used successfully among a child sample (Hill et al., 2009).

Food Consumption.

Pre- and post- lunch tray photos were coded to determine amount of food consumed by trained research assistants. The visual estimation scale used was based on the quarter-waste visualization method outlined in Comstock et al. (1981). The approach involved two coders rating each food item on a six-point percentage scale (1 – 100% consumed, 2 – 75% consumed, 3 – 50% consumed, 4 – 25% consumed, 5 – 10% consumed, and 6 – 0% consumed). A third coder was used to resolve discrepancies between coders one and two. Although some studies suggest that visual estimation is significantly less accurate compared to direct weight measurement (Martins, Cunha, Rodrigues, & Rocha, 2014), many others attest to that efficiency, reliability and validity, and comparability of visual estimation to direct observation and weighing trays (Navarro, Singer, Leibovitz, Krause, & Boaz, 2014; Taylor, Yon, & Johnson, 2014; Swanson, 2008; Connors & Rozell, 2004; Williamson et al., 2004; Williamson et al., 2003).

Food items were broken down into dietary categories (fruits, vegetables, and main entrée), and percentage consumed was calculated for each dietary category, as well as, overall meal for each participant.

Diet Quality.

The Nutrition Data System for Research (NDSR) was used to determine the diet quality of the consumed portions of each child's lunch. Specifically, the pre- and post- lunch photos were coded again, with each food item coded using an 11-point percentage scale ranging from 0% to 100% consumed. The NDSR is a dietary analysis program developed by the University of Minnesota Nutrition Coordinating Center (NCC) and uses the NCC Food and Nutrient Database

(includes over 18,000 foods) to calculate the nutritional breakdown (i.e. kcals, grams of fat and sugar consumed, portion of total calories from fruits and vegetables, etc.) of consumed foods (Probst & Tapsell, 2005; Sievert et al., 1989). Individual “menus” were created for each participant containing the coded food items. From these menus, the NDSR was able to calculate a Healthy Eating Index (HEI) score. The HEI is an index of how closely the diet quality of consumed food matches the 2010 federal dietary guidelines of America (Guenther et al., 2013). According to Guenther and colleagues (2013), the HEI is a valid and reliable measure of diet quality. The NDSR has been used successfully in past research to evaluate fruit and vegetable consumption among children at school (Harrington, Kohler, McClure, & Franklin, 2009).

Child BMI z-scores.

Height and weight were collected for each participant. Children were asked to remove their shoes, all items from their pockets, and heavy clothing (i.e. hoodies or jackets). Height was measured in centimeters using a stadiometer. Weight was measured in pounds using a digital weight scale. Standardized BMI was calculated for each child based on gender- and age-specific growth charts provided by the CDC (Kuczmarski et al., 2002). Growth charts were computed based on normative samples from the 1960s through the 1990s. Syntax for the statistical software STATA, provided by the CDC, was used to calculate the BMI z-scores for our sample.

Analytic Design and Statistical Analysis

All data will be plotted to assess normality, and winsorization will be used to address any outliers. If distributions continue to be skewed, appropriate data transformations will be performed to meet the assumption of normality. DD scores will be calculated as the ratio between the total number of immediate reward selections over the number of delayed reward selections. RRV_{food} will be calculated as the switch point value, or point where children are no

longer willing to work for the unhealthy food and switch to the healthy alternative. Food consumption will be calculated as the proportion of food consumed from what was selected (grams) for each child. ANOVAs and t-tests will be conducted to identify if any significant differences exist between demographic variables (i.e. sex, grade, and race/ethnicity) and our predictor variables. If significant results are found, then the demographic variable will become a co-variate and be controlled for in proceeding analyses.

Hypothesis I: RRV_{food} will be a significant predictor of child BMI z-score, diet quality, and calorie intake.

Three separate simple linear regressions will be used to assess the predictive value of RRV_{food} on BMI z-score, diet quality, and calorie intake.

Hypothesis II: DD will be a significant predictor of child BMI z-score, diet quality, and calorie intake.

Three separate simple linear regressions will be used to assess the predictive value of DD on BMI z-score, diet quality, and calorie intake.

Hypothesis III: Higher RRV_{food} scores will predict higher calorie intake, lower diet quality, and higher BMI z-scores, but especially for children with steeper DD scores.

Three separate moderation models will be tested: one for each criterion (BMI z-score, diet quality, and kcals) with RRV_{food} and DD being predictors in all models. A description of the analytic steps for one of the moderation models is below. This process will be repeated for each outcome variable.

A nested linear regression will be conducted to assess moderation. One, restricted, model will have diet quality as the criterion and RRV_{food} and DD as predictors. A second, full, model

will have diet quality as the criterion variable and have DD, RRV_{food} , and $DD * RRV_{\text{food}}$ as predictors. This interaction coefficient will be used to test the moderation model, with DD as the moderator between RRV_{food} and diet quality.

It is predicted that RRV_{food} and DD will be significant predictors of diet quality, BMI z-score, and kcals in each of the first, restricted models. Specifically, for every one unit increase in RRV_{food} and/or DD, diet quality will decrease by a certain amount, and BMI z-score and kcals will increase by a certain amount. Then, each second, full, model will show the main effects of RRV_{food} and DD, but also a significant interaction term. A simple slopes test will be conducted to identify if the slope of the simple regression equation, for low, average, and high DD, is significantly different from zero. Values for low, average, and high will correspond to one standard deviation below the mean, the mean, and one standard deviation above the mean on DD. The simple slopes are predicted to all be significantly different from zero. Results from these initial tests will show that RRV_{food} leads to worse diet quality and higher BMI z-score and kcal, but especially for those who have higher DD scores. A follow up test will be conducted for each model to assess the amount of unique variance accounted for by the interaction. Specifically, a *F*-test will be conducted comparing the change in R^2 between the restricted and full model.

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Appendix A

Delay Choice Questionnaire - CHILD

Instructions: For each of the following choices, please imagine each reward and circle which one you would rather get: the smaller reward today, or the larger reward after waiting for a period of time. Please carefully think about each of these choices.

*** For this one, the reward is the snack food that you picked in the earlier task as the one you like the most:**

1. Would you rather get **one today** or **two today**?
2. Would you rather get **one today** or **two tomorrow**?
3. Would you rather get **one today** or **two in 5 days**?
4. Would you rather get **one today** or **two in 1 week**?
5. Would you rather get **one today** or **two in 2 weeks**?
6. Would you rather get **one today** or **two in 4 weeks**?
7. Would you rather get **one today** or **two in 3 months**?
8. Would you rather get **one today** or **two in 6 months**?
9. Would you rather get **one today** or **two in 1 year**?

Appendix B

For each question below please tick whether you would prefer to work for one of your favourite cookies or one of your favourite apples. Make sure you read each question carefully to see how much work is required to get one biscuit or one sticker.

	Would you prefer to...	
1	Push the button 20 times for a cookie <input type="checkbox"/>	OR Push the button 20 times for an apple <input type="checkbox"/>
2	Push the button 40 times for a cookie <input type="checkbox"/>	OR Push the button 20 times for an apple <input type="checkbox"/>
3	Push the button 60 times for a cookie <input type="checkbox"/>	OR Push the button 20 times for an apple <input type="checkbox"/>
4	Push the button 80 times for a cookie <input type="checkbox"/>	OR Push the button 20 times for an apple <input type="checkbox"/>
5	Push the button 100 times for a cookie <input type="checkbox"/>	OR Push the button 20 times for an apple <input type="checkbox"/>
6	Push the button 120 times for a cookie <input type="checkbox"/>	OR Push the button 20 times for an apple <input type="checkbox"/>
7	Push the button 140 times for a cookie <input type="checkbox"/>	OR Push the button 20 times for an apple <input type="checkbox"/>
8	Push the button 160 times for a cookie <input type="checkbox"/>	OR Push the button 20 times for an apple <input type="checkbox"/>
9	Push the button 180 times for a cookie <input type="checkbox"/>	OR Push the button 20 times for an apple <input type="checkbox"/>
10	Push the button 200 times for a cookie <input type="checkbox"/>	OR Push the button 20 times for an apple <input type="checkbox"/>
11	Push the button 220 times for a cookie <input type="checkbox"/>	OR Push the button 20 times for an apple <input type="checkbox"/>
12	Push the button 240 times for a cookie <input type="checkbox"/>	OR Push the button 20 times for an apple <input type="checkbox"/>