Comparing and Intervening on Preference for and Reinforcing Value of Edibles Across Adolescents and Young Adults

by

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Abstract

Obesity has been identified as an epidemic by the US Centers for Disease Control and Prevention since 1999. This epidemic is of concern because obesity is correlated with adverse health outcomes such as hypertension, diabetes, metabolic syndrome, and cancer. Research on determinants of this epidemic indicate (a) childhood obesity sets a trajectory for obesity in adulthood and (b) changes in caloric quantity in the food supply may have given rise to this epidemic. Moreover, this epidemic may occur at higher rates for populations who are of low socioeconomic status, have limited access to nutrient-dense foods, or both. One such population that may be uniquely impacted by this epidemic is justice-involved youth. The proposed series of studies seeks to build upon previous research on food reinforcement and behavioral demand by: (a) comparing demand for edibles across two groups and (b) evaluating the effect of a nutrition intervention on demand among justice-involved adolescents. In Study 1, participants in two groups completed preference assessments for high- and low-energy density edibles and corresponding hypothetical purchasing tasks. Behavioral demand was compared between- and within-groups. In Study 2, a sample of justice-involved adolescents received instruction related to nutrition. Following intervention, participants completed preference assessments and hypothetical purchasing tasks again. Findings from Study 1 indicated (a) between-group differences in behavioral demand and (b) within-group differences in demand for high- versus low-energy density edibles. Findings from Study 2 indicate nutrition intervention may have a limited effect on behavioral demand. Implications for future research are discussed.

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Table of Contents

List of Tables

List of Figures

Chapter 1

Literature Review

Obesity Epidemic

Obesity was first characterized as an epidemic in the United States by the US Centers for Disease Control and Prevention (CDC) in 1999 (Koplan & Dietz, 1999). In their editorial, Koplan & Dietz acknowledged the role of environmental determinants of obesity and solicited preventative efforts that focused on environmental determinants. Since then, a large body of literature has emerged regarding the environmental determinants of obestity, adverse health outcomes associated with obesity, and prevention of obesity.

Obesity has been defined as excessive adiposity which may adversely impact health (World Health Organization, 2018). Thus, obesity is defined by its problematic correlation with adverse health outcomes. Specifically, the relation between obesity and increased blood pressure (i.e., hypertension) is well-established (Hall et al., 2010; Hall et al., 2015; Landsberg et al., 2013) and is estimated to account for 65-78% of cases of hypertension (Shariq & McKenzie, 2020). Increased adiposity has also been identified as a precursor to diabetes mellitus (i.e., Type 2 diabetes; Boles et al., 2017; Guilherme et al., 2019) and the prevalence of this relation is expected to increase globally over the next decade (Ampofo & Boateng, 2020). Moreover, the adverse effects of obesity combine to give rise to other clinical complications.

When hypertension and diabetes caused by obesity become part of a combination of conditions including glucose intolerance and dyslipidemia, this is known as metabolic syndrome and is also linked to obesity (Abete et al., 2011; Fall & Ingelsson, 2014). Perhaps most concerningly, evidence suggests obesity is a predictor of cancer (Goodwin & Stambolic, 2015). Cancer has been identified as the leading cause of death globally (World Health Organization,

2022) and has been described as an emerging epidemic (Ugai et al., 2022). Taken together, these studies demonstrate the far-reaching adverse effects of obesity, causing concern for many national and global health agencies.

In an effort to treat and prevent obesity, many scholars have directed their focus to identifying the causes of obesity. As Kopel and Dietz (1999) called for, research regarding the causes of obesity has focused on environmental determinants. Subsequently, this research has identified three primary causes of obesity: (a) the food environment (Hall, 2018), (b) decreased physical activity (Church & Martin, 2018), and (c) behavioral factors (Davis et al., 2018). Hall (2018) notes recent changes in the nutritional characteristics of the food supply and subsequent changes in normative eating behaviors may give rise to increased rates of obesity. That is, Hall suggests obesity can be attributed to the increased consumption of processed foods which are calorically dense and conveniently available, leading to their rapid overconsumption. Church & Martin (2018) note that engagement in consistent recreational exercise has not changed substantially over the last several decades, but occupational activity has decreased with the advent of technological efficiencies. Thus, they attribute obesity, in part, to the decrease in occupation-related activity. The food environment and decreased occupation-related activity have been referred to as “the big two” causes of the obesity epidemic. But Davis et al. (2018) consider other behavioral factors such as increased sleep deprivation, smoking cessation, and delay discounting as important aspects to consider in the obesity epidemic. Notably, all three of these perspectives involve environmental determinants that can potentially be modified to mitigate this epidemic. Despite differing perspectives, obesity researchers seem to agree in one key area: efforts to prevent obesity should begin in childhood.

Indeed, many of the first federally-funded efforts to prevent obesity targeted the behavior of children. These efforts included programs promoting healthy eating behaviors and increased physical activity (Centers for Disease Control, 2011). As a result, researchers developed a set of recommendations for preventing obesity in childhood to include increasing nutrition education in public settings such as schools and community organizations (Koplan et al., 2005). Subsequently, many of these programs specifically targeted schools as a primary setting for delivery of obesity prevention programs (Brener et al., 2006; Kolbe et al., 2001; Merlo et al., 2015). These studies identified two important trends: (a) obesity appears to be related to socioeconomic status (SES; Li & Hooker, 2010; Rogers et al., 2015; Wang et al., 2006) and (b) adolescence is an important developmental period in preventing obesity (Das et al., 2017; Gordon-Larsen et al., 2010; Kwon et al., 2015; Pont et al., 2017).

As an example of the role of the food environment as an environmental determinants of obesity, low SES communities also have limited access to nutrient-dense foods. Such communities have been described as "food deserts," characterized by low-income and low-access thresholds as defined by the US Department of Agriculture (Chen et al., 2016). Food deserts have been associated with increased levels obesity (Ghosh-Dastidar et al., 2014; Chen et al., 2016), further compounding adverse health outcomes for adolescence in these communities. Given the epidemic uniquely impacts individuals residing in low SES communities (such as food deserts) and adolescence has been identified an important period for preventing obesity, interventions targeting the intersection of these populations are critical to resolving this epidemic.

Adolescent Obesity

Adolescence marks a period of substantial changes in physical, cognitive, and social development. Health in adolescence is impacted by mental and physical health in childhood and sets a trajectory for health in adulthood (Canavan & Fawzi, 2019). As the final developmental stage before adulthood, adolescence is a pivotal period for intervening on behavioral habits that will persist into adulthood. Growing evidence suggests diets of high nutritional quality may improve physical and cognitive growth during adolescence (Gordon-Larsen et al., 2010). Moreover, some research suggests improved nutrition in adolescence may improve academic performance (Burrows et al., 2017).

In a recent report, Alabama ranked 5th in childhood obesity across the U.S. (State of Childhood Obesity, 2020). This report indicated 21.8% of children ages 10 to 17 years in Alabama are obese or overweight. Adolescent obesity has been linked to an increased risk of hypertension, diabetes, asthma, and premature mortality (Reilly & Kelly, 2011). In addition, diets high in sodium have been linked to an increase in depressive symptoms (Mrug et al., 2019). Adolescents in Alabama may reside in counties specifically characterized by significantly higher rates of poverty, obesity, and limited food access (Gaines, 2014; Lane & Davis, 2022; Sisiopiku & Barbour, 2014). Based on aforementioned programs targeting prevention of obesity in childhood, decreasing adolescent obesity might be achieved through development of programs to teach proper nutrition.

Justice-Involved Youth

Notably, justice-involved youth are more likely to come from low-income families (Gatti et al., 2009) and may reside in communities with limited access to nutrient-dense foods. Thus, this population may be more susceptible to environmental determinants of obesity. Given the aforementioned research regarding prevention programs delivered in schools and community settings, it seems reasonable to include nutritional training protocols in rehabilitative programming for residents of juvenile facilities. Developing such programming could start with evaluating preference and motivation for nutritional foods.

There are at least four broad reasons why adolescents in JRTFs might benefit from programs to teach proper nutrition. First, individuals in JRTFs may engage in severe problem behavior such as aggression and are likely to receive psychotropic medication to decrease problem behavior (Anderson et al., 2021; Cohen et al., 2014; Lyons et al., 2013). Psychotropic medications may produce undesirable side effects such as weight gain (Barnett & Zayas, 2019; Solmi et al., 2020). Weight gain as a result of psychotropic medication use may be exacerbated by poor diet. Second, many adolescents in residential facilities often perform below grade level academically (Kroll et al., 2002). Conversely, diets of high nutritional quality may improve academic performance in adolescents (Burrows et al., 2017). Thus, by improving nutrition, it is possible academic performance may also improve for individuals in this population.

Third, adolescents who have been adjudicated are more likely to have at least one psychiatric diagnosis along with comorbid mental illness (Lader et al., 2003; Robertson et al., 2004). Specifically, it is estimated that up to 25% of adolescents who have been adjudicated display moderate depression (Domalanta et al., 2013). Moreover, diets high in sodium may contribute to increases in depressive symptoms in adolescents (Mrug et al., 2019). Conversely, diets of high nutritional quality are associated with improved behavioral outcomes (Oddy et al., 2009) and improved mental health (Jacka et al., 2011).

Fourth, adolescents in JRTFs are more likely to come from low-income families (Gatti et al., 2009) and are likely to experience multiple instances of trauma (Harrelson et al., 2017). Both of these features are associated with poor health outcomes (Evans & Kim, 2007). Despite these challenges, teaching nutritional skills has been associated with improved health outcomes in children and adolescents from low-income families (Joyner et al., 2017; Neff et al., 2009). Moreover, nutritionally dense foods are associated with increased feelings of satiety (Rolls et al., 2005; Williams et al., 2014). Thus, teaching adolescents nutrition skills may attenuate weight gain, improve academic performance, improve mental health, and enhance feelings of satiety. Such skills may include teaching adolescents to identify and select nutrient-dense foods when available. For example, selecting fresh fruit as a side instead of macaroni and cheese at lunch in the cafeteria. These skills are particularly important for adolescents in JRTFs who often are from low-income families and thus uniquely impacted by the obesity epidemic. Such a program should start with evaluating preference for and reinforcing value of various edibles with this population.

Behavioral Economics

To study essential value of a reinforcer (i.e., strength), behavioral scientists often use a behavioral economics approach. The term, first coined by Kapel and Winkler (1972), refers to a collaborative efforts by psychololgists and economists. Different from a purely behavior analytic approach, behavioral economics is informed by economic principles (Camerer et al., 2004). Although traditional economic principles might suggest humans make rational decisions, a behavioral economics approach suggests humans make irrational decisions (Thaler & Sunstein, 2008). This is evident to the casual observer of human behavior.

For example, young adults often drive home from a bar inebriated rather than calling a ride-sharing service, despite the dangerous consequences of driving while under the influence. A parent scrolls through their social media feed rather than attending to their child on the playground, regardless of the perils of jungle gyms. Individuals consume foods high in fat and sugar, despite the long-term health complications associated with their consumption. In each of these scenarios, behavioral economics may be used as one approach to understand the essential value of reinforcers in a variety of highly contextual scenarios. Moreover, it has been suggested behavioral economics should be used in public policy to bring about environmental modifications that give rise to desirable behavior change (Hansen & Jespersen, 2013; Thaler & Sunstein, 2008).

Law of Demand

The main principle underlying behavioral economics is the law of demand. The law of demand implies consumption is inversely related to unit price (Samuelson & Nordhaus, 1985). That is, consumption of a specified commodity decreases as the price of that commodity increases (and vice versa). For example, if a pack of cigarettes costs $7 one week and the price increases by five dollars the following week, the law of demand suggests fewer packs will be sold. Conversely, if the pack of cigarettes is on sale for $3 in a given week, the law of demand suggests a greater number of packs will be sold. Furthermore, the law of demand posits the relative reinforcing value of a commodity will decrease if the unit price becomes excessively high.

In behavioral economics, the law of demand provides a conceptual framework for understanding behavioral mechanisms underlying behavioral demand. These same behavioral mechanisms underly behavior observed during preference and reinforcer assessments commonly used in behavior analytic interventions (e.g., Davis et al., 2021; DeLeon et al., 1996; Durand et al., 1989; Fisher et al., 1992; Roane et al., 1998; Roscoe et al. 1999). Said differently, the law of demand also provides a conceptual framework for understanding responding in traditional operant methods. However, traditional operant methods may not be feasible, either ethically or logistically, in some contexts. Thus, behavioral economics researchers have developed analogue tasks to evaluate reinforcer value.

Tasks

In a seminal study, Jacobs and Bickel (1999) used hypothetical purchasing tasks (HPTs) to evaluate consumption of commodities at progressively increasing prices. Specifically, Jacobs and Bickel asked opioid-dependent outpatients to self-report a hypothetical quantity of cigarettes or bags of heroin they would purchase at varied, ascending prices. For example, in the first question, participants were asked "How many cigarettes would you buy if cigarettes cost $0.01?" Prices increased with each question up to a price of $1,120.00. Researchers delivered tasks under three conditions: (a) when only cigarettes were hypothetically available, (b) when only bags of heroin were hypothetically available, and (c) when cigarettes and bags of heroin were concurrently hypothetically available.

To control for hypothetical contexts, Jacobs and Bickel (1999) instructed participants to complete the HPT under specific assumptions including: (a) they were not in treatment, (b) the only available drugs were the drugs hypothetically purchased, (c) the cigarettes and heroin were for their consumption only, (d) cigarettes and heroin purchased could not be sold or traded, and (e) the cigarettes and heroin purchased were for personal consumption within a 24-hour period.

Researchers developed demand curves based on responses to evaluate the relation between consumption and unit price. Demand curves for each condition conformed to the quantitative model proposed by Hursh et al. (1988). Moreover, Jacobs and Bickel (1999) suggested questionnaires like the one used in their study may prove useful in other clinical applications.

Of note, Jacobs and Bickel (1999) proposed several advantages of simulation experiments over traditional methods for evaluating reinforcer efficacy. First, simulation experiments may be more convenient in contexts that present logistical or ethical dilemmas for researchers. For example, simulation experiments allow for evaluation of illicit substances in individuals recovering from substance use disorders without providing access to such substances. In addition, simulation experiments allow researchers to evaluate a wide variety of stimulus contexts which may control human behavior such as large quantities of money or long periods of time. Traditional methods may be logistically limited by time or use of large quantities of a commodity. Finally, simulated procedures such as the HPT are based on traditional methods for evaluating reinforcer efficacy. This gives rise to conceptually systematic simulation procedures that produce results, which can be interpreted using the same terms and concepts for evaluating outcomes produced using traditional methods. Said differently, progressively increasing prices used in HPTs mimic the progressive ratio schedule used in traditional reinforcer assessments and such results may be used to evaluate reinforcer efficacy. These characteristics of HPTs proffer them as potentially useful in clinical settings in which logistics limit the use of traditional methods of reinforcer assessment.

Clinical Utility

Translational research is the application of principles and procedures of basic science to solve socially relevant issues. It has been suggested the future of behavior analysis depends on both basic and applied arms adopting translational methods to maintain social relevance (Critchfield, 2011, Mace & Critchfield, 2010). Translating behavioral methodology involves creative application of basic procedures to address socially relevant issues (Vollmer, 2011).

In recent years, behavior analytic procedures have become more efficient due to advancements in technology. For example, researchers have used hypothetical tasks as measures of reinforcer efficacy for a variety of items and activities. HPTs have been suggested as a convenient and effective method for evaluating motivation for various commodities. For example, using a sample of undergraduate students, Broadbent and Dakki (2015) developed the Internet Purchase Task to evaluate demand for internet access in problematic and nonproblematic internet users. Jarmolowicz et al. (2016) also used a sample of undergraduates, but used an HPT wherein participants purchased hypothetical sexual encounters with partners identified through preference assessment. HPTs have also been used to evaluate demand for food. Epstein et al. (2018) used HPTs to evaluate behavioral demand for edibles of various energy densities in a sample of adult.

Only a few studies have evaluated HPTs with adolescents (e.g., Barnes et al., 2020; Murphy et al., 2011) and these studies have primarily focused on substance use. Moreover, to our knowledge, no studies using HPTs have been conducted with adolescents in JRTFs. With this in mind, evaluating essential value of different foods among adolescents may be a useful first step in understanding the relation between the food environment and behavioral demand for foods. As much of the aforementioned research on HPTs has been conducted with undergraduate populations, it may be useful to compare the two groups to better understand (a) if undergraduate populations can continue to be used as a comparison to clinical populations and (b) if demand among adolescents begins to simulate demand in the next developmental stage of young adulthood. Evidence to the contrary would suggest intervention to improve behavioral demand among adolescents is warranted. Thus, research is warranted in this clinical population of concern.

To date, HPTs have primarily been used as tools for research; however, HPTs may ultimately have clinical utility. Moreover, previous researchers have called for behavioral economics to be used in clinical settings (Reed et al., 2013). Based on the aforementioned studies, we propose using HPTs to evaluate motivation for edibles in justice-involved youth at a JRTF. The proposed series of studies can be considered a translation of behavioral methdology as they seek to improve the clinical utility of a tool typically used for research purposes. We propose using HPTs to (a) compare behavioral demand across two groups and (b) evaluate the effects of a nutrition intervention on demand among justice-involved adolescents.

Hypotheses

The proposed series of studies seek to evaluate preference and motivation for edibles for two groups: (a) justice-involved adolescents (JIA) and (b) undergraduate students at a large state university. In Study 1, participants in each group completed rank order preference assessments for high- and low-energy density edibles. Then, participants completed HPTs for the highest and lowest preferred edibles in each category. For Study 1, our hypotheses were: (a) adolescents would demonstrate greater behavioral demand than undergraduate students in some conditions and (b) within both groups, participants would demonstrate greater behavioral demand for highly preferred, high energy density edibles than for highly preferred, low energy density edibles. In Study 2, a subsample of the JIA group also received nutrition intervention to teach proper nutrition skills and edible selections. Nutrition intervention included: (a) learning to read a nutrition label, (b) identifying food groups, and (c) identifying health benefits associated with consumption of nutrient-dense edibles. Following intervention, participants completed rank-order assessments and HPTs again. In study 2, we hypothesized the nutrition intervention would increase behavioral demand for highly preferred, low energy density edibles.

Chapter 2

Experiment I

Purpose

The purpose of Experiment I was to use HPTs to evaluate differences in behavioral demand for edibles between JIA in a JRTF and undergraduates at a large state university. Participants in both groups were recruited from the same geographical region.

Methods

Participants

Participants were recruited from two settings: (a) a JRTF and (b) undergraduate psychology courses at a local state university. In the JRTF, the researcher obtained consent from a state Department of Youth Services (DYS) representative who serves as residents' legal guardian before recuiting and assenting JIA. Constraints of the facility often limit access to computer and internet. That is, residents of the facility are sometimes restricted from accessing computers and internet access is often disrupted. Thus, researchers conducted sessions on the campus of the JRTF using two modalities: (a) accessing the online assessment via computers within the facility and directing participants to respond to the instructions on screen or (b) administering the assessment using paper and pencil and instructing participants to respond following written instructions. To the researcher's knowledge, no previous literature has demonstrated a meaningful difference in findings based on differences in HPT modality.

For undergraduate students, researchers recruited participants using SONA, an online platform for undergraduate research recruitment and participation. Researchers only included data for participants between 18 and 25 years of age. Using this platform, participants provided consent and accessed the online assessment remotely.

Setting

JRTF

Researchers conducted assessments using Qualtrics™ remotely or in a quiet room or office within the JRTF. Quiet rooms and offices within the facility typically contained a desk, a desktop computer, and three to five chairs. Researchers conducted assessments using paper and pencil in the multipurpose room of each dorm. Each multipurpose room was furnished with up to 24 chairs and desks, a large table, and a television. In compliance with the policies of the JRTF, two researchers were present and wearing cotton or surgical masks for all assessments conducted in-person to protect participants and researchers from possible exposure to COVID-19. For both assessment modalities, researchers monitored participants for the duration of the assessment. At the start of the assessment, the researcher read the written assessment instructions aloud, then instructed participants to answer the questions to the best of their ability. If a participant asked questions about the assessment, the researcher responded vaguely and redirected them back to the assessment. If the participant attempted to converse with researchers on unrelated topics, researchers informed the participant they could talk after the assessment session.

State University

For undergraduates attending the large state university, researchers administered the assessment remotely and asynchronously using Qualtrics™. Thus, the settings in which participants complete the assessment varied.

Dependent Variables

Researchers collected data on the following dependent variables: (a) nutritional data on all edibles used in the experiment, (b) rank order of edibles, (c) hypothetical quantity purchased at each price, (d) price of edibles evaluated, (e) duration of assessment, and (f) participant demographic information (i.e., age, race/ethnicity, sex). Table 1 contains descriptions of all dependent variables and their corresponding assessments. Researchers also collected data on the duration of each assessment as reporting time estimates may improve the clinical utility of HPTs. Figure 1 contains a flowchart detailing the order of assessments for each participant.

Nutritional Data

Edibles identified for use with both groups in this study were selected based on two criteria: (a) feasibility of storage in the JRTF and (b) energy density (ED). First, researchers identified edibles typically stored and provided to residents of the JRTF. Researchers also identified edibles that could be stored at this facility based on their shelf stability (i.e., dry goods), but were not stored and provided at the facility at the time of the study. Then, researchers conducted an internet search to find an image of the nutrition label for each edible using a local online grocer. Researchers downloaded and saved each nutrition label image and recorded nutritional data including: (a) kilocalories per serving, (b) grams per serving, (c) grams of fat per serving, (d) grams of protein per serving, (e) grams of carbohydrates per serving, (f) grams of sugar per serving. Using these data, researchers calculated ED for each edible by dividing kilocalories per serving by grams per serving. As determined by Epstein et al. (2007) and Rolls et al. (2005), edibles with an ED ≤ 2 were categorized as low ED. Edibles with an ED ≥ 3 were categorized as high ED. The researcher did not include edibles with an ED between two and three in the experiment. Assessments for both groups of participants included the same edibles. Table 2 includes nutritional data for all edibles included in the assessment.

Preference Assessments

Researchers designed a Qualtrics^{TM} (Version March 2021) survey to conduct preference assessments using a rank order arrangement. Images of edibles were presented on screen and participants were instructed to click and drag pictures to corresponding numbers indicating rank from highest to lowest preference (i.e., #1 indicated highest preference and #7 indicated lowest preference). For participants completing the assessment using paper and pencil, researchers conducted the assessment using procedures identical to those described in Davis et al. (2021). That is, researchers provided pictures and names of each edible and a space for participants to write in each edible name in order from first to seventh, wherein the edible listed first was the most preferred edible. Researchers conducted the rank order preference assessment across two conditions: high ED edibles and low ED edibles, in that order.

Hypothetical Purchasing Tasks

Hereafter, participants in both groups completed four HPTs. Each participant completed one HPT for each of the following conditions: (a) high preferred high energy density (HP-HED) edibles, (b) low preferred high energy density (LP-HED) edibles, (c) high preferred low energy density (HP-LED) edibles, and (d) low preferred low energy density (LP-LED) edibles, in that order. The four edible HPTs assessed prices, which were similar to those used in Epstein et al. (2018), and were presented in ascending order (i.e., $0.00, $0.01, $0.05, $0. 13, $0.25, $0.50, $0.1, $2, $3, $4, $5, $6, $11, $35, $70, $140, and $280). Participants responded by either entering or writing an integer in the text response box presented on screen or paper.

Analytical Plan

Researchers exported de-identified data from the Qualtrics™ survey to encrypted files on a password-protected laptop computer. Researchers manually entered data from assessments conducted in-person into the same data files. Then, researchers evaluated data using statistical analyses.

Statistical Analysis

All statistical analyses were conducted using RStudio (Version 1.4.1717) and SPSS (Version 28.0). Specifically, the researcher used the R package *beezdemand* (v0.1.0; Kaplan et al., 2019) to (a) screen for nonsystematic responding, (b) fit data to two models of demand, and (c) derive indices of demand based upon selected models (Kaplan et al., 2019). Specifically, data were screened for unsystematic responding using the criteria outlined by Stein et al. (2015). That is, the package uses a three-criterion algorithm based on (a) relative change scores (i.e., requires log-unit changes in consumption to remain relative to log-unit changes in price), (b) bounce (i.e., requires increases in consumption do not exceed 25% of initial consumption as prices increase by less than or equal to 10%), and (c) reversals from zero (i.e., requires two consecutive zero consumption values are not followed by a nonzero consumption value). The researcher also excluded data for any participants who did not complete the survey or were above the age cutoff for the undergraduate group. Specifically, 13 participants were excluded from the JIA group and 16 participants were excluded from the undergraduate group based on criteria.

After screening data, the researcher (a) winsorized (Blaine, 2018) consumption values and (b) fitted and evaluated two models of demand to the data. The researcher fitted and evaluated the equations proposed by Hursh and Silberberg (2008) and Koffarnus et al. (2015) using a two-stage approach (Kaplan et al., 2021). Then, the researcher compared log-transformed demand metrics between- and within-groups using Welch's independent samples *t*-tests.

Nutritional Comparison

Based on nutritional data collected, the researcher calculated mean kilocalories and mean grams of macronutrients ans sugar for each edible category. Thereafter, the researcher calculated the cost per serving (i.e., price divided by number of servings per container) and cost per calorie (i.e., cost per serving divided by kilocalories per serving). Researchers used these data to conduct a cost analysis to compare high and low ED edibles.

Results

Researchers recruited a total of 77 JIA and 124 undergraduates. After screening for inclusion criteria, incomplete data sets, and unsystematic data, the researcher conducted all subsequent analyses using data for 64 participants in the JIA group and 108 participants in the undergraduate group. Participants completed assessments in 11 min and 9 min on average in the JIA and undergraduate groups, respectively. The researcher collected data on racial identity for undergraduate students based on overall estimates provided by SONA for the specific population of undergraduate students currently using SONA at the local university within the last academic year. Thus, these racial identities are estimates of the identities of students included in the study. Similarly, administrators at the JRTF provided limited data on the average age and racial identities of participants in the JIA group. Specifically, the researcher was permitted to collect data on age and racial identity for some participants within the facility, but not all. Thus, sample sizes in the demographic data for both groups may be different than sample sizes reported in statistical analyses. Demographic data for each group are displayed in Table 3.

Behavioral demand is multifaceted, thus the researcher evaluated demand using several demand metrics using *beezdemand*. Specifically, these included: (a) intensity, (b) alpha, (c) breakpoint, (d) price maximum, and (e) output maximum. Descriptions of each of these demand metrics are listed in Table 4. The researcher fit data for each condition of the HPTs to each of the equations proposed by Hursh and Silberberg (2008) and Koffarnus et al. (2015). Based on r^2 values, data in Table 5 indicate the Koffarnus et al. model fit best for data both conditions, for both groups. All subsequent demand metrics were observed or derived using the Koffarnus et al. equation to evaluate the research questions specific to the present study.

Nutritional Data

After identifying seven edibles to be included in each edible condition in the rank order assessment, researchers calculated (a) kilocalories per serving, (b) grams per serving, (c) grams of fat per serving, (d) grams of protein per serving, (e) grams of carbohydrates per serving, (f) grams of sugar per serving, (g) cost per serving, (h) cost per calorie, and (i) energy density for each edible. The mean values for each of these variables by energy density group are listed in Table 6. Overall, these data indicate low ED edibles were lower in kilocalories, fat, carbohydrates, and sugar per serving on average. Notably, the mean grams of protein per serving was equal across high and low ED categories. In addition, low ED foods were lower in cost per serving and cost per calorie, on average.

Between-Groups Comparisons

Our first hypothesis was that adolescents would demonstrate greater behavioral demand than undergraduate students in the HP-HED condition. To test this hypothesis, the researcher first derived demand metrics using the specified model. Then, the researcher conducted Welch's independent samples t-tests to compare mean differences on all five demand metrics of interest across groups. In the HP-HED condition, the JIA group demonstrated greater intensity (M = 52.79, SD = 46.47) than undergraduate group (M = 12.71, SD = 19.01) and the mean difference was significant, $t(145.45) = -9.89$, $p < .01$, $d = -1.51$. The rate of change in elasticity of the demand curve in the HP-HED condition (i.e., alpha) was smaller for the JIA group (M = .026, SD = .09) than for undergraduate group (M = .045, SD = .0175) and the mean difference was significant, $t(118.73) = 5.62$, $p < .01$, $d = 0.91$. The JIA group demonstrated breakpoints of greater value in the HP-HED condition (*M.* = 57.72, *SD* = 91.51) than the undergraduate group (*M* = 17.63, *SD* = 53.12) and the mean difference was significant $t(118.51) = -5.16$, $p < .01$, d = -084. The JIA group demonstrated smaller price maximums (*M* = 41.23, *SD* = 84.54) compared to the undergraduate group (*M* = 104.00, *SD* = 132.58) and the mean difference was significant, $t(169.81) = 2.46$, $p < 0.05$, $d = 0.36$. Finally, the adolescent group demonstrated greater output maximum (*M* = 32.07, *SD* = 31.94) compared to the undergraduate group (*M* = 8.21, *SD* = 13.00), and the mean difference was significant, $t(123.45) = -9.19$, $p<0.1$, $d = -1.47$. Overall, these findings suggest the JIA group demonstrated greater behavioral demand than the undergraduate group in the HP-HED HPT condition and the difference between these groups was significant on all five demand metrics. Table 7 displays t-test comparisons for between-groups comparisons in the HP-HED condition. Figure 2 depicts demand curves of these between-groups comparisons.

Within-Groups Comparisons

We hypothesized participants would demonstrate greater behavioral demand for high ED edibles than low ED edibles. To compare behavioral demand for each edible category, the researcher conducted Welch's independent samples *t*-tests within groups to evaluate mean differences between demand metrics in the HP-HED and HP-LED conditions, for each group.

JIA Group

The JIA group demonstrated greater intensity in the HP-LED condition (*M* = 58.41, *SD* = 52.73) than in the HP-HED condition (*M* = 52.79, *SD* = 46.48). However, the mean difference was not significant. The JIA group also demonstrated greater rate of change in elasticity of the demand curve (i.e., alpha) in the HP-LED condition (*M* = .07, *SD* = .045) than in the HP-HED condition (*M* = .02, *SD* = .09). Note, smaller values indicated greater behavioral demand. The mean difference was not significant. The JIA group demonstrated breakpoints of lesser value in the HP-HED condition (*M* = 25.46, *SD* = 35.54) compared to the HP-LED condition (*M* = 26.84, *SD* = 36.50) and the mean difference was not significant. The adolescent group demonstrated greater price maximum in the HP-LED condition (*M* = 73.66, *SD* = 115.15) compared to the HP-HED condition (*M* = 41.23, *SD* = 84.54) and the mean difference was significant, $t(137.9) = -1.98$, $p<.05$, $d = -0.33$. Finally, the JIA group demonstrated greater output maximum in the HP-HED condition (*M = 32.97, SD*=31.94) than in the HP-LED condition (*M* = 24.27, *SD* = 25.39); however, the difference was not significant. These findings indicate demand was greater in the HP-HED condition for some metrics, but not all. Demand metrics for comparison within the JIA group can be found in Table 8. Figure 3 depicts demand curves of this within-group comparison of the HP-HED and HP-LED HPT conditions for the JIA group.

Undergraduate Group

Undergraduate students demonstrated greater intensity in the HP-LED condition (*M* = 13.69, *SD* = 21.96) compared to the HP-HED condition (*M* = 12.71, *SD* = 19.02). The mean difference was not significant. Undergraduate students also demonstrated greater rate of change in elasticity across the demand curve in the HP-LED condition (*M* = 1.68, *SD* = 0.06) compared to the HP-HED condition (*M* = .045, *SD* = .17). However, the mean difference was not significant. The undergraduate group demonstrated greater breakpoints in the HP-HED condition (*M* = 17.63, *SD* = 53.12) compared to the HP-LED condition (*M* = 10.49, *SD* = 30.44). The mean difference was not significant. The undergraduate group demonstrated greater price maximums in the HP-HED condition (*M* = 104.00, *SD* = 132.57) compared to the HP-LED condition (*M=97.*04, *SD* = 16.24); however, the mean difference was not significant. Finally, the undergraduate group demonstrated greater output maximum in the HP-HED condition (*M* =

8.21, *SD* = 13.00) than in the HP-LED condition (*M* = 7.26, *SD* = 8.35). Again, the mean difference was not significant. These data indicate participants in the undergraduate group display somewhat similar demand for high preferred edibles across ED category. Demand metrics for within-group comparisons for the undergraduate group can be found in Table 9. Figure 4 depicts demand curves of this within-group comparison of the HP-HED and HP-LED HPT conditions for the undergraduate group.

Conclusions from Experiment I

Overall, these findings indicate the JIA group demonstrated different features of behavioral demand compared to the undergraduate group. Specifically, the JIA group demonstrated significantly greater behavioral demand in the HP-HED condition compared to undergraduate students based on measures of intensity, rate of change in elasticity, breakpoint, price maximum, and output maximum. Moreover, this difference was significant for all five demand metrics analyzed, indicating participants in the JIA group demonstrated greater behavioral demand than those in the undergraduate group in the HP-HED condition. These findings confirm our first hypothesis.

Our second hypotheses concerning within-group comparisons were only partially supported. That is, within the JIA group, mean differences existed between the HP-HED and HP-LED condition, however, these differences were only significant for one of five demand metrics of interest. Participants in the undergraduate group displayed greater differences in behavioral demand based on ED; however, these differences were not significant. Taken together, findings from Experiment I indicate (a) the JIA group demonstrates significantly different behavioral demand for edibles compared to the undergraduate group and (b) behavioral demand within this group may differ based on ED alone.

Experiment II

Purpose

The purpose of Experiment II was to evaluate the effect of a nutrition intervention on behavioral demand in the HP-LED condition among adolescents in the JRTF.

Method

Participants

Prior to conducting Experiment II, the researcher sought approval to conduct nutrition intervention within the JRTF on a dorm-by-dorm basis. Administrative staff at the facility approved the use of the nutrition intervention with only a subset of the JIA group from Experiment I that had illegal sexual behavior. Thus, we refer to them as the Adolescents with Illegal Sexual Behavior (AISB) group. The researcher recruited participants from Experiment II from only the population of AISB residing at the JRTF.

Assessments

Participants in Experiment II completed rank order assessments and HPTs exactly as described in Experiment I. In addition, participants in Experiment II completed an Internet Purchasing Task (IPT) identical to that described in Broadbent and Dakki (2015). The purpose of the IPT was to serve as a control condition, for which we hypothesized the nutrition intervention would have no effect. In Experiment II, researchers conducted these assessments before and after the nutrition intervention.

Nutrition Intervention

The researcher developed the nutrition intervention by adapting curriculum from Bandini et al. (2012). This curriculum was developed and validated as part of a nutrition and activity education (NAE) program for adolescents with intellectual disabilities (ID) (Fleming et al., 2008). Specifically, Fleming et al. modified family-based behavioral interventions demonstrated to be effective with typically developing children to meet the needs and repertoires of individuals with ID. This curriculum was demonstrated to be effective for individuals with ID in community settings with parental involvement (Curtin et al., 2013) and when delivered by an interdisciplinary team (Lauria & Waldrop, 2020). Although residents within the JRTF in this study may not be diagnosed with ID, their profiles and repertoires may bear similarity to the populations in the aforementioned studies. Said differently, adolescents in JRTFs typically demonstrate below-average intellectual functioning (Falligant et al., 2017). Thus, this curriculum may be appropriate for this population as well.

The published curriculum from Bandini et al. (2012) recommended trainers deliver intervention in 60-min sessions across 10 weeks. In the present study, researchers delivered intervention as lessons in 60-min sessions, one to two times per week, across 9 to 10 weeks within JRTF dorms. Table 10 provides a list of the nutrition topics covered each week. Intervention sessions were conducted in the same setting of the JRTF as in Experiment I. The researcher delivered intervention to participants as a group. Participation was voluntary and the researcher communicated this to participants at the beginning of *each* intervention session. Thus, some participants were not in attendance for every intervention session. During each intervention session, the researcher performed the following tasks:

1. Distributed pencils and folders containing printed instructional materials to each participant.
2. Delivered a PowerPoint™ presentation.
3. Facilitated interteaching among participants.
4. Instructed participants to complete an in-class activity related to the weekly topic.

Each participant folder contained: (a) guided notes packets, (b) interteaching worksheets, and (c) a syllabus detailing the lessons and activities for each week. For some intervention sessions, the researcher provided an in-class activity as well. Examples of printed instructional materials can be found in Appendix A.

During PowerPoint ™ presentations, the researcher instructed participants to complete a guided notes packet (Kourea et al., 2019). Guided notes packets contained printed PowerPoint™ slides with blank spaces for key words. The research instructed participants to write each key word that corresponded to the PowerPoint™ slide presented. During interteaching, the researcher assigned participants to groups of two to three participants and instructed them to take turns teaching topics indicated on the interteaching worksheet (Boyce & Hineline, 2002; Brown et al., 2014). These sessions typically lasted 10 to 15 min, thus they can be considered an abbreviated form of interteaching. Participants wrote their answers on the interteaching worksheet. For sessions including an in-class activity, the researcher instructed participants to use class materials (e.g., local menus, empty food packaging, etc.) to engage in hands-on activities and answer questions on the in-class activity worksheet. At the conclusion of each nutrition intervention session, the researcher delivered edible exemplars of low-energy density snacks (e.g., pickles, sugar free pudding, fruit cups) to reinforce attendance at the intervention session. Hereafter, the researcher collected pencils, folders, and printed instructional materials.

Data Collection

Assessment

Researchers conducted assessment of behavioral demand before and after the nutrition intervention was delivered using the same procedures as described in Experiment I. That is, behavioral demand for edibles was evaluated using HPTs delivered using paper and pencil or an online survey. In addition, participants in Experiment II completed IPTs in a similar fashion. Data for both assessment modalities were recorded and entered into Excel™ workbooks on a secure computer.

Instructional Materials

Following each nutrition intervention session, researchers recorded data on percentage of correct responses to guided notes, interteaching worksheets, and in-class activity worksheets using completed printed instructional materials (i.e., permanent products produced by participants). Correct responses for guided notes were defined as textual responses that had point-to-point correspondence with key words in the PowerPoint™ presentation. Correct responses for interteaching were defined as textual responses that completely answered the question on the interteaching worksheet. Correct responses for the in-class activity were defined as textual responses that completely answered the question on the class activity worksheet. Data were converted to percentage of correct responses by dividing the total number of correct responses by the total number of opportunities and multiplying by 100.

Treatment Integrity

During delivery of the nutrition intervention, a secondary researcher collected data on treatment integrity as the primary researcher delivered instruction. Treatment integrity was collected on 61% of nutrition intervention sessions. Data were converted to a percentage of correct components by dividing the total opportunities treatment components were implemented correctly by the total number of opportunities treatment components were delivered correctly and incorrectly and multiplying by 100. The mean treatment integrity score across intervention sessions was 97.96%.

On-Task Behavior

The secondary researcher also collected data on on-task behavior during interteaching using 10-s momentary time sampling (MTS; Devine et al., 2011; Rapp et al., 2008; Schmidt et al., 2013). On-task behavior was defined as participant oriented toward classwork materials (e.g., guided notes or interteaching worksheet) or engaging in verbal behavior related to course content (e.g., intraverbals, tacts, or textuals related to nutrition), excluding instances when the participant was oriented toward unrelated paperwork, the television, or engaging in verbal behavior not related to course content (e.g., looking at the wall, intraverbals related to video games) for 3 s or more. This definition also excluded participants writing or drawing anything unrelated to course content (e.g., drawing pictures, writing name repetitively, etc.). Data collected for on-task behavior were converted to percentage of intervals on-task by dividing the total number of intervals on-task by the total number of intervals observed and multiplying by 100.

Interobserver Agreement

A tertiary observer also collected data on on-task behavior. Interobserver agreement (IOA) was calculated using the interval-by-interval method by dividing the total number of agreements by the total number of agreements plus disagreements and multiplying by 100. IOA was collected on approximately 75% of sessions. The mean IOA score across lessons was 87.25%.

Social Validity

Following completion of the nutrition intervention, researchers collected data on social validity ratings from participants in Experiment II using a social validity questionnaire adapted from Lauria (2018). This adapted social validity questionnaire can be found in Appendix B. A secondary researcher distributed social validity questionnaires and pencils, read written instructions aloud, and collected completed the social validity questionnaires from participants.

The primary researcher remained outside the room during social validity data collection to possible observer reactivity. Responses were collected anonymously and researchers recorded the mean score on each statement.

Results

Table 11 lists and describes each dependent variable evaluated in Experiment II. The primary dependent variable for Experiment II was the change in behavioral demand for edibles in the HP-LED condition following the nutrition intervention. The secondary dependent variables for Experiment II were the percentage of correct responses on printed instructional materials (e.g., guided notes, interteaching) and percentage of intervals on-task during interteaching.

Researchers recruited a total of 60 participants from the AISB group to participate in Experiment II. After screening for incomplete data sets and unsystematic data, the researcher conducted all subsequent analyses using data for 42 participants pre-intervention and compared these to data for 31 participants post-intervention. Demographic data for Experiment II are displayed in Table 12.

Behavioral Demand

As described in Experiment I, the researcher evaluated behavioral demand across several demand metrics using *beezdemand* in R Studio (Kaplan et al., 2019). Specifically, demand metrics evaluated included: (a) intensity, (b) alpha, (c) breakpoint, (d) price maximum, and (e) output maximum. Descriptions of each of these demand metrics are listed in Table 4. Again, the researcher fit data for each condition of the HPTs to each of the equations proposed by Hursh and Silberberg (2008) and Koffarnus et al. (2015). Based on r^2 values, data in Table 13 indicate the Koffarnus et al. model fit best for data across all HPT conditions. Thus, all subsequent demand metrics were observed or derived using the Koffarnus et al. (2015) equation to evaluate the research questions specific to Experiment II. As in Experiment I, all inferential analyses were performed using log transformed values of demand metrics.

Within-Group Comparison

First, the researcher compared behavioral demand within the AISB group across the HP-HED and HP-LED conditions. For comparison, the researcher conducted Welch's independent *t*-tests to evaluate mean differences in the HP-HED and HP-LED conditions, prior to intervention. The AISB demonstrated greater intensity in the HP-HED condition (M = 30.74, SD = 20.50) than in the HP-LED condition (M = 14.77, SD = 9.18) and the difference was significant, $t(51.51)$ = 3.49, p<.01, d = 0.76. The AISB group also demonstrated greater rate of change in elasticity in the HP-HED condition (M = 0.03, SD = 0.14) compared to the HP-LED condition (M = 0.024, SD = 0.05), and the mean difference was significant, $t(42.04)$ = -17.46, p<.01, d = -3.74. The AISB group also demonstrated greater break points in the HP-HED condition(M = 74.06, SD = 99.60) than in the HP-LED condition (M = 56.10, SD = 91.27) and the mean difference was significant, $t(70.04)$ = 2.10, p<.05, d = 0.46. The AISB group demonstrated lower price maximum in the HP-HED condition (M = 34.80, SD = 73.50) than in the HP-LED condition (M = 86, SD = 119.64) and the mean difference was significant, $t(81.55)$ = -2.29, p<.05, d = -0.50. Finally, the AISB group demonstrated greater output maximum in the HP-HED condition (M = 96.23, SD = 108.21) than in the HP-LED condition (M = 80.20, SD = 186.56) and the mean difference was significant, $t(81.30)$ = -2.37, p<.05, d = 0.51. Table 14 displays comparisons of these demand metrics and Figure 5 displays demand curves this within-group comparison of HP-HED and HP-LED HPT conditions prior to intervention for the AISB group.

HP-LED Condition

In the HP-LED condition of the HPTs, the AISB group demonstrated greater intensity post-intervention (*M* = 15.54, *SD* = 9.44) than pre-intervention (*M* = 14.78, *SD* = 9.18). However, the mean difference was not significant. The AISB group also demonstrated greater rate of change in elasticity of the demand curve (i.e., alpha; larger values indicate lower demand) post-intervention (*M* = .05, *SD* = .2) than pre-intervention (*M* = .02, *SD* = .05). The mean difference was not significant. The AISB group demonstrated breakpoints of lesser value post-intervention (*M* = 39.28, *SD* = 3.86) compared to pre-intervention (*M* = 56.10, *SD* = 91.27) and the mean difference was not significant. The AISB group demonstrated lesser price maximum post-intervention (*M* = 79.23, *SD* = 121.17) compared to pre-intervention (*M* = 86, *SD* = 119.64) and the mean difference was not significant. Finally, the AISB group demonstrated lesser output maximum post-intervention (*M* = 57.35*, SD*=91.02) compared to pre-intervention (*M* = 72.32, *SD* = 96.17); however, the difference was not significant. Demand metrics for comparison for the HP-LED condition pre- and post-intervention can be found in Table 15. Figure 6 depicts demand curves of this comparison for the AISB group.

Given participation in nutrition intervention was voluntary, some participants did not participate consistently. That is, some participants attended some portions of intervention, but not all. Of the 42 participants who participated in nutrition intervention, the researcher identified those whom (a) completed the pre-intervention tasks and (b) completed at least 80% of the guided notes and interteaching assignments, and (c) completed the post-intervention tasks indicating a high level of participation. Subsequently, the researcher conducted analyses to evaluate the effect of nutrition intervention for participants who engaged in high levels of participation with nutrition intervention. Two participants from this subset were released from the facility before the post-intervention assessment was conducted, thus data for pre- and post-intervention analyses included 15 and 13 participants, respectively. Given the small number of participants within this subset, the researcher conducted Kruskall-Wallis H tests to evaluate the effect of nutrition intervention on demand metrics in the HP-LED HPT condition. Because this test does not rely upon assumptions of normality, analyses were conducted using raw values for demand metrics rather than log transformed values. Results from this subgroup indicate the extent of the effect of the intervention was stronger for this group, despite no significant differences.That is, there were no significant differences in demand metrics obtained pre- versus post-intervention for this subgroup of participants with high levels of participation; however, the raw demand values indicate an effect. These findings are summarized in Table 16. Figure 7 depicts demand curves of this of HP-LED HPT condition pre- and post-intervention for this subgroup of participants with high levels of participation.

IPT Condition

The purpose of the IPT was to serve as a control commodity for which we hypothesized the nutrition intervention would not have an effect. Again, the researcher compared behavioral demand in the IPT condition using the same methods as described in the HP-LED condition analysis, using Welch's t-tests to compare responding pre-intervention and post-intervention. In the IPT condition, the AISB group demonstrated greater intensity for access to internet in post-intervention (M = 4.94, SD = 0.24) compared to pre-intervention (M = 4.73, SD = 0.97) and the mean difference was not significant. The AISB group demonstrated greater break point values post-intervention (M = 18.8, SD = 9.3) compared to pre-interventions (M = 18.25, SD = 9.9) and the mean difference was not significant. This group demonstrated lesser rate of change in demand for internet access post-intervention (M = 0.11, SD = 0.2) as compared to pre-intervention (M = 0.15, SD = 0.5) and the mean difference was not significant. This group demonstrated lesser price maximum post-intervention (*M* = 5.51, *SD* = 3.9) compared to pre-intervention (*M* = 6.70, *SD* = 3.98) and the mean difference was not significant. Finally, this group demonstrated lesser output maximum post-intervention (*M* = 17.96, *SD* = 14.89) compared to pre-intervention (*M* = 22.40, *SD* = 18.21) and the mean difference was not significant. Table 17 displays these comparisons by demand metric.

Instructional Materials

The researchers collected data on correct responding on instructional materials by scoring permanent products produced by participants. That is, as participants completed guided notes and interteaching worksheets, researchers scored their written responses. Figure 8 displays mean percentage of correct responding on guided notes across lessons. The researcher set a criterion for review at 80% meaning the researcher would remediate any lesson for which the mean percentage of correct responses was less than 80%. Across all nine lessons, participants maintained responding well above this criterion. Thus, no remedial lessons were warranted. Overall, these data indicate a stable trend with high levels of correct responding across lessons.

Data were collected in the same manner for responding on interteaching worksheets. Figure 9 depicts mean percentage of correct responding on interteaching worksheets across lessons. The researcher set the same criterion for interteaching worksheets. That is, data indicating the mean percentage of correct responding would result in a remedial lesson. These data indicate responding across all nine lessons did not meet this criterion and no remedial lessons were warranted. These data indicate high levels of correct responding with minimal variability across lessons.

On-Task Behavior

Researchers collected data on on-task behavior during interteaching across all lessons using 10-s MTS. The mean percentage of intervals on-task was calculated by summing the total number of intervals on-task across interteaching groups, dividing by the total number of intervals observed across groups, and multiplying by 100. Figure 10 depicts the mean percentage of intervals on-task across lessons. These data indicated levels of on-task behavior were high and slightly variable.

Social Validity

Figure 11 depicts mean ratings for each statement included in the social validity questionnaire. As this questionnaire was distributed at the end of the intervention and voluntary, only 30 participants completed this form. Data for all 30 participants indicate generally high ratings for every statement.

Notably, statement 14 had the lowest mean rating. This statement was "I discussed topics covered in Healthy U with peers and staff throughout the week, when I wasn't in a Healthy U session." This low rating indicates participants were not discussing these topics with other people they saw regularly in their natural environment. In addition, statement three had the highest mean rating. These data indicate participants strongly agreed with the statement "The course was organized and easy to follow along with." This finding indicates participants found the curriculum structure used for this intervention was well-organized.

Conclusions from Experiment II

Taken together, these data indicate the nutrition intervention was implemented with high fidelity, as indicated by several dependent variables. Specifically, data indicate high levels of correct responding on instructional materials, high levels of on-task behavior during interteaching, and high levels of treatment integrity. Moreover, the three statements with the highest social validity ratings indicated participants found (a) the intervention to be well-organized, (b) the researcher was engaging, and (c) they enjoyed attending sessions. These findings indicate participants were engaged with the nutrition intervention and the intervention was well-received. However, the effect of the intervention was limited.

Our primary hypothesis, that nutrition intervention would increase behavioral demand for edibles in the HP-LED HPT condition was not completely supported by statistical analysis. Although there was an increase in demand observed for some demand metrics (i.e., intensity), this increase was not present for all demand metrics, not sufficient to produce statistically significant results, or both. This may be due to shifts in participants' ability to engage with intervention. That is, participants who (a) were assigned to the dormitory in the middle of the intervention or (b) only attended some of the intervention did not receive the nutrition intervention at a level high enough to affect behavioral demand.

For those participants who engaged with the nutrition intervention at a high level (i.e., completed ≥80% of instructional materials), subsequent analyses indicated behavioral demand for edibles in the HP-LED HPT condition increased following intervention. Specifically, this increase in demand was observed for four out of five demand metrics. Although these differences did not produce statistically significant findings, behavioral demand did change to some extent, as a result of nutrition intervention. These findings are supported by data from the IPT, indicating behavioral demand for access to internet did not change as a result of the nutrition intervention (i.e., a control condition). Additional implications are discussed.

Discussion

To our knowledge, this series of studies is the first of their kind to evaluate behavioral demand for edibles among JIA and to evaluate the effects of nutrition intervention for this population using behavioral demand tasks. Given this population is underserved in many ways, this series of studies contributes to the broader literature regarding improving conditions of confinement for this population. Moreover, as HPTs have primarily been used as tools for research, this series of studies contributes to the call for translational research to assess the clinical utility of behavioral economic methodology (Reed et al., 2013).

In Experiment I, results confirm both hypotheses, to some extent. As it relates to our first hypothesis, the JIA group did demonstrate greater behavioral demand for edibles in the HP-HED condition than undergraduates across all five demand metrics (i.e., intensity, elasticity, breakpoint, and output maximum). For all five demand metrics, the mean difference between groups was significant. Said differently, these findings indicate JIA group demonstrated greater amplitude and persistence in demand for HP-LED edibles compared the undergraduate group.

Our second hypothesis in Experiment I was only partially confirmed. That is, within the JIA group, participants demonstrated greater behavioral demand on two out of five demand metrics comparing HP-HED edibles versus HP-LED edibles (i.e., alpha, output maximum). However, within the undergraduate group, participants demonstrated greater behavioral demand on four out of five demand metrics for HP-HED edibles versus HP-LED edibles. Although the majority of mean differences between these demand metrics were not statistically significant within either group, the overall differences in demand may reflect relevant differences between these two groups.

On the economic continuum, participants in the JIA group can be considered to be operating within a closed economy. That is, their access to edibles is limited by the restrictions of the facility and may lack variety. By contrast, participants in the undergraduate group may consistently have access to a wider variety of edibles. As a result of these differences, the extent to which participants in the JIA group discriminate between edibles in a hypothetical task may be limited. In other words, participants in the JIA group may experience a greater establishing operation for a variety of edibles for which they have limited access. Thus, their behavioral demand is greater across all types of edibles, regardless of energy density. Moreover, their access to edibles included in the LED condition may be limited, making this group of edibles more valuable due to their novelty. Indeed snacks provided in the facility included many of the edibles from the HED category and only a few edibles from the LED category. This effect of the economy continuum is well-established (Hursh, 2014; Imam, 1993).

Importantly, these findings should be considered along with nutritional data from Experiment I. Nutritional data on edibles included in Experiment I indicated edibles in the LED category were lower in kilocalories, fat, carbohydrates, and sugar per serving on average. Moreover, edibles in the LED category cost less per serving and per calorie, on average. Given participants in the JIA group did not demonstrate significantly different levels of demand for edibles based on energy density, these findings support increasing access to LED edibles within the JRTF. Especially when used as reinforcers for appropriate, prosocial behavior. Moreover, for practitioners obligated to minimize use of harmful reinforcers, these findings support careful consideration of the use of reinforcers. These findings also comport with recent research regarding the reinforcing efficacy of nutrient-dense edibles as compared to calorie-dense edibles (Kronfli et al., 2020). Consistent, large of consumption of HED edibles is associated with adverse health outcomes such as hyptertension, diabetes, and metabolic syndrome (Abete et al., 2011; Boles et al., 2017; Shariq & McKenzie, 2020). By contrast, increased access to LED edibles may be an important component in leveraging the developmental trajectory of adolescents to improve health outcomes in adulthood.

Experiment I is not without limitations. First, despite the comparisons made between the JIA and undergraduate groups, their stark demographic differences should be noted. Although the age range between the two groups overlapped, the difference in mean age was 3.64 years. In addition, we did not collect data on socioeconomic status (SES) of participants in either group. With respect to age, older participants may have more experience making purchases and managing money, thus influencing responding in a task that inherently involves monetary values (i.e., HPTs). Moreover, individuals enrolled in an undergraduate institution are more likely to come from high SES families (Klugman & Lee, 2019). Conversely, JIA often come from low SES families (Gatti et al., 2009). These differences in age and SES may impact responding in the HPT. However, the two groups were from the same general geographic region. As result, the extent to which these two groups are comparable is limited. Future research should seek to identify a comparison group matched to the JIA group on factors such as age, SES, and geographic region. By identifying such a group, future studies may better estimate the extent to which JIA differ from their peers in measures of behavioral demand.

Second, this study only evaluated HPTs using an ascending price arrangement with no additional manipulations. Other studies have evaluated the effect of experimental manipulations on behavioral demand such as cue exposure, reinforcer magnitude, price density, and purchase type (Acuff et al., 2020; Roma et al., 2016). Such studies indicate these experimental manipulations may impact amplitude of demand, persistence of demand, or both. As previous research on behavioral demand with JIA is limited, evaluating such manipulations was beyond the scope of the present studies. Nonetheless, future research should systematically evaluate the effect of these experimental manipulations on behavioral demand among JIA. Such studies would improve our understanding of the generality of previous research and our understanding of this unique population.

In Experiment II, within-group comparisons for the AISB group indicated participants displayed significantly greater demand in the HP-HED condition than in the HP-LED condition on three out of five demand metrics. These findings indicate intervention to increase the value of LED edibles. Our hypothesis that nutrition intervention would increase behavioral demand for edibles in the HP-LED condition was only partially confirmed. Data for all participants in the AISB group indicated behavioral demand for edibles in the HP-LED condition improved following intervention for only one out of five demand metrics (i.e., intensity); however, this difference was not significant. Given the limited participation of some participants, subsequent analyses were conducted for a subset of the AISB group who completed at least 80% of instructional material or more, indicating high levels of participation in the intervention. For this subset of participants, the effect of the nutrition intervention was greater: behavioral demand for HP-LED edibles improved on four out of five demand metrics (i.e., intensity, breakpoint, price maximum, and output maximum). These findings indicate high levels of participation may be required for the nutrition intervention to affect amplitude and persistence in behavioral demand.

For those participants for which the nutrition intervention had some effect, we hypothesize components of the intervention such as (a) learning to read a nutrition label, (b) identifying food groups, and (c) identifying health benefits associated with consumption of nutrient-dense edibles served as augmentals (Hayes et al., 2001; Hayes et al., 2004; Törneke, 2010; Zettle & Hayes, 1982). That is, nutritional information related to the benefits of LED edibles served to increase the reinforcing consequences of their selection and consumption. Augmentals, a type of rule, can be classified as motivative (i.e., affecting motivating operations) or formative (i.e., function-altering; Kissi et al., 2017). To be specific, the nutrition intervention in this study was likely working as a motivative augmental. Although rule-governance repertoires were not explicitly evaluated in this study, interventions intended to improve rule-governed behavior may be important for this population. As this population is often characterized by the limitations of their rule-governed repertoires, expanding and generalizing rule-governance may have far-reaching consequences.

As previously discussed, the food environment has been identified as one possible cause of the obesity epidemic (Hall, 2018). The food environment may include changes to the food supply, limited access to nutrient-dense foods, or both, as in the case of food deserts. It has been suggested that improving access to nutrient-dense foods, subsidizing their consumption, or both may improve demand for these foods. However, recent research suggests altering access and subsidization alone may not be enough to increase consumption of nutrient-dense foods. In a study by Allcott et al. (2019), researchers found these modifications to the food environment only resulted in small increases in consumption and suggested differences in demand contributed more to changes in consumption. Thus, interventions seeking to improve consumption of LED edibles may be more effective when they focus on methods for increasing demand, as in the present study.

Some limitations of Experiment II should be noted. First, this study took place in a treatment facility wherein therapeutic activities were available to students throughout the day and included activities that may be more preferable to participants than nutrition intervention. Such activities included individual therapy sessions, occupational training programs, and religious education groups. In addition, residents moved to different dorms not yet receiving the intervention or were released during the course of the intervention and preventing their continued engagement. Indeed, the results from Experiment II indicate the effect of the nutrition intervention was primarily evident in data for participants with high levels of participation. Thus, practitioners looking to implement interventions related to behavioral demand should consider the level of participation necessary to produce meaningful outcomes. That is, interventions targeting behavioral demand may require high levels of participation for their effects to be detectable in statistical analyses.

Second, Experiment II was conducted with a specific subgroup of participants included in Experiment I. In Experiment I, researchers recruited JIA from across the facility. In Experiment II, researchers only recruited AISB within the facility. In part, this was due to limitations of administrative policies within the facility. Nonetheless, the extent to which our findings may have generality to other populations is limited. Future research should seek to evaluate the effect of nutrition intervention on JIA in different facilities and programs, which may have different behavioral repertoires than participants in the present study.

Finally, participants in Experiment II were court-ordered to participate in a treatment program within the facility. As part of the therapeutic milieu of this program, a token economy was developed and monitored by licensed behavior analysts. Within this token economy, participants could earn points daily for appropriate behavior and trade them weekly for reinforcers such as edibles. The present study did not evaluate the extent to which nutrition intervention affected token exchange behavior for edibles within this token economy. Although it was beyond the scope of this study, future research should evaluate the effect of nutrition intervention on token exchange behavior in an effort to evaluate behavioral changes beyond the hypothetical task.

For many adolescents who are incarcerated, effective nutrition intervention may have far-reaching consequences. Adolescents residing in detention facilities often come from low-income families (Gatti et al., 2009) and experience trauma at greater rates throughout their childhood (Harrelson et al., 2017). Moreover, many of these adolescents come from areas that have been characterized as food deserts that have been associated with increased rates of obesity (Ghosh-Dastidar et al., 2014; Chen et al., 2016), further compounding negative health outcomes for this population. Together, these features predispose this population to by exceptionally affected by the obesity epidemic and the resulting adverse health outcomes (Evans & Kim, 2007). By contrast, increased consumption of nutrient-dense foods has been associated with positive health outcomes such as increased satiety (Rolls et al., 2005; Williams et al., 2014), improved academic performance (Burrows et al., 2017), and improved behavioral and mental health (Oddy et al., 2009; Jacka et al., 2011). Future research should continue to seek to improve nutrition interventions targeting this population. By improving the nutritional repertoires of this vulnerable population, we may have a positive impact on their developmental trajectories following release from detention.

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Table 1

Dependent Variables used in Experiment I

Dependent Variable	Definition	Time of Data Collection
Rank order	Order of preferred foods from most to least preferred.	Preference assessment
Demand Metrics	Variables that characterize behavioral demand.	Hypothetical purchasing task
Nutritional Data	Comparison of edibles by energy density group including cost per serving and cost per calorie.	All

Table 2

Nutritional Data for Edibles used in Rank Order Preference Assessment

Energy Density Level	Edible Name	Grams per Serving	Servings per Package	Calories per Serving	Fat (g) per Serving	Carbs (g) per Serving	Protein (g) per serving	Cost per Serving	Energy Density
Low	VanHolten's Dill Pickle	28	60	0	0	0	0	$0.30	0
Low	Sugar Free Strawberry JELL-O Cups	89	8	10	0	0	1	$0.46	0.112
Low	Great Value Unsweetened Applesauce Cups	113	6	60	0	15	0	$0.23	0.530
Low	Sugar Free Chocolate and Vanilla Swirl JELL-O Pudding Cups	103	8	60	1.5	10	1	$0.46	0.582
Low	Pearls Black Olive Snack Packs	15	8	15	1.5	1	0	$0.43	1
Low	Great Value Peach Fruit Cups	113	12	70	0	17	1	$0.41	0.619
Low	StarKist Tuna Creations Tuna Salad	85	1	80	1.5	3	13	$1.00	0.941

Energy Density Level	Edible Name	Grams per Serving	Servings per Package	Calories per Serving	Fat (g) per Serving	Carbs (g) per Serving	Protein (g) per serving	Cost per Serving	Energy Density
High	Zapps VooDoo Potato Chips	28	2.5	150	8	17	2	$0.51	5.36
High	FunYuns Onion Flavored Rings	21.3	10	110	4.5	14	1	$0.45	5.16
High	Moon Pie Double Decker Chocolate Marshmallow Sandwich	78	6	300	7	55	4	$1.76	3.86
High	Little Debbie Honey Bun	85	8	350	19	42	4	$0.38	4.12
High	Nabisco Nutter Butter Cookies	28	16	140	6	19	2	$0.21	6.07
High	Golden Flake Sweet Heat Barbeque Potato Chips	28	4.6	150	8	17	2	$0.36	5.36
High	Nabisco Oreo Cookies	34	16	160	7	25	1	$0.23	4.70

Table 3

Demographic Data for Groups in Experiment 1

	JIA Group	Undergraduate Group
Sex		
Male	100% (64)	20.37% (22)
Female	0% (0)	79.63% (86)
Age		
Mean	16.81	20.45
SD	1.28	1.95
Range	14, 19	18, 25
Racial identity		
Black	29.17% (14)	3.96% (31)
White	66.67% (32)	86.19% (674)
Hispanic	2.08% (1)	1.79% (14)
Asian	0% (0)	2.15% (17)
American Indian	2.08% (1)	0.26% (2)

Table 4

Description of Demand Metrics

Demand Metric	Description	Observed or Derived
Intensity	Responding at price of $0.00	Observed
Alpha	Rate of change in slope (i.e., elasticity) across demand curve	Derived
Breakpoint 0	First price at which responding is zero	Observed
Price Maximum	Price at which slope of demand curve is -1, indicating a shift from inelasticity to elasticity in demand	Observed
Output Maximum	Maximum responding at price maximum	Observed

Table 5

Model Candidates and R^2 Comparisons in Experiment I

Model	R^2	Rank	HPT Condition	Group
Koffarnus et al. (2015)	0.987	1	HP-HED	Undergraduate
Hursh & Silberberg (2008)	0.867	2		
Koffarnus et al. (2015)	0.979	1	HP-LED	
Hursh & Silberberg (2008)	0.881	2		
Koffarnus et al. (2015)	0.961	1	HP-HED	JIA
Hursh & Silberberg (2008)	0.655	2		
Koffarnus et al. (2015)	0.956	1	HP-LED	
Hursh & Silberberg (2008)	0.710	2		

Table 6

Nutrition Data by Energy Density Group

Variable	High ED *M*	Low ED *M*
Kilocalories per Serving	194.3	42.1
Grams per Serving	43.2	78
Fat (g) per Serving	8.2	0.64
Carbohydrates (g) per Serving	27	6.6
Protein (g) per Serving	2.3	2.3
Sugar (g) per Serving	7.6	3.8
Cost per Serving ($USD)	0.55	0.47
Cost per Calorie ($USD)	0.02	0.009
Energy Density	4.9	0.54

Note. *M* = mean value for each variable by group

Table 7

Between-Groups Comparisons in the HP-HED Condition

Demand Metric	*t*-statistic	*Undergraduate Group Mean (SD)*	*JIA Group Mean (SD)*	*Cohen's d*
Intensity of Demand	-9.89**	12.71 (19.01)	52.79 (46.47)	-1.51
Alpha	5.62**	0.045 (0.175)	0.026 (0.09)	0.91
Breakpoint 0	-5.16**	17.63 (53.12)	57.72 (91.51)	-0.84
Price Maximum	2.46*	40.00 (132.58)	41.23 (84.54)	0.36
Output Maximum	-9.19**	8.21 (13.00)	32.97 (31.94)	-1.47

Note. For all comparisons, **p*<.05, ***p*<.01. Values presented in raw form. Log transformed for inferential analysis to achieve normality.

Table 8

Within-Group Comparisons in the JIA Group

Demand Metric	*t*-statistic	*HP-HED Condition Mean (SD)*	*HP-LED Condition Mean (SD)*	*Cohen's d*
Intensity of Demand	0.44	52.79 (46.48)	58.41 (52.73)	
Alpha	0.45	0.02 (0.09)	0.07 (0.45)	
Breakpoint 0	0.11	25.46 (35.54)	26.84 (36.50)	
Price Maximum	-1.98*	41.23 (84.54)	73.66 (115.15)	-0.33
Output Maximum	-1.82	32.97 (31.94)	24.27 (25.39)	

Note. For all comparisons, *p<.05. Values presented in raw form. Log transformed for inferential analysis to achieve normality.

Table 9

Within-Group Comparisons in the Undergraduate Group

Demand Metric	*t*-statistic	*HP-HED Condition Mean (SD)*	*HP-LED Condition Mean (SD)*
Intensity of Demand	1.26	12.71 (19.02)	13.69 (21.96)
Alpha	-1.03	0.045 (0.17)	1.68 (0.06)
Breakpoint 0	1.26	17.63 (53.12)	10.49 (30.44)
Price Maximum	0.57	104.00 (132.57)	97.04 (16.24)
Output Maximum	-0.05	8.21 (13.00)	7.26 (8.35)

Note. Values presented in raw form. Log transformed for inferential analysis to achieve normality.

Table 10

Nutrition Intervention Curriculum Topics by Week

Week	Topic
1	Intro to Nutrition and MyPlate
2	Fruits, Vegetables, and Dairy
3	Grains and Protein
4	Meal Planning: Variety and Mixed Dishes
5	Added Sugars
6	Added Fats
7	Healthy Choices
8	Healthy Snacks versus Treats
9	Eating Out and Around Town

Table 11

Dependent Variables used in Experiment II

Dependent Variable	Description	Time of Data Collection
Rank order	Order of preferred foods from most to least preferred.	Pre/post intervention
Demand Metrics	Variables that characterize behavioral demand as measured by hypothetical purchasing task.	Pre/post intervention
Percent Correct Written Responses on Guided Notes Packets	Textual responses that have point-to-point correspondence with key words in the PowerPoint™ presentation	Nutrition intervention sessions
Percent Correct Written Responses on Interteaching Worksheets	Textual responses that completely answer the question on the interteaching worksheet	Nutrition intervention sessions
Percent correct Written Responses on In- Class Activity Worksheets	Textual responses that completely answer the question on the class activity worksheet	Nutrition intervention sessions
Percent Intervals On-task During Interteaching	Participant is oriented toward and looking at either the classwork (e.g., guided notes or interteaching worksheet) or engaging in verbal behavior related to course content (e.g., intraverbals, tacts, or textuals related to nutrition). Excludes instances when student is oriented toward unrelated paperwork for 3s or more, the television, or engaging in verbal behavior not related to course content (e.g., looking at the wall, intraverbals related to video games). Excludes student writing/drawing anything unrelated to course content (e.g., drawing pictures, writing name repetitively, etc.). Collected using 10-s momentary time sampling.	Nutrition intervention sessions
Treatment Integrity	Percentage of treatment components delivered correctly	Nutrition intervention sessions
Interobserver agreement	Percentage of observation intervals primary and secondary observers had agreement	Nutrition intervention sessions

Table 12

Demographic Data for Participants in Experiment II

	Pre-Intervention	Post-Intervention
Sex		
Male	100% (42)	100% (31)
Female	0% (0)	0% (0)
Age		
Mean	16.02	16.16
SD	1.07	1.24
Range	14, 18	14, 19
Racial identity		
Black	33.33% (14)	35.48% (11)
White	61.90% (26)	58.06% (18)
Hispanic	2.38% (1)	3.22% (1)
Asian	0% (0)	0% (0)
American Indian	2.38% (1)	3.22% (1)

Table 13

Model Candidates and R^2 Comparisons in Experiment II

Model	R^2	Rank	HPT Condition	Group
Koffarnus et al. (2015)	0.963	1	HP-HED	AISB
Hursh & Silberberg (2008)	0.735	2		
Koffarnus et al. (2015)	0.960	1	Pre-intervention HP-LED	
Hursh & Silberberg (2008)	0.573	2		
Koffarnus et al. (2015)	0.988	1	Post-intervention HP-HED	
Hursh & Silberberg (2008)	0.898	2		

Table 14

Within-Group Comparisons in the AISB Group

Demand Metric	*t*-statistic	*HP-HED Condition Mean (SD)*	*HP-LED Condition Mean (SD)*	*Cohen's d*
Intensity of Demand	3.49**	30.74 (20.50)	14.77 (9.18)	0.76
Alpha	-17.46**	0.03 (0.14)	0.024 (0.05)	-3.74
Breakpoint 0	2.10*	74.06 (99.60)	56.10 (91.27)	0.46
Price Maximum	-2.29*	34.80 (73.50)	86 (119.64)	-0.50
Output Maximum	-2.37*	96.23 (108.21)	80.20 (186.56)	0.51

Note. For all comparisons, *p<.05, **p<.01. Values presented in raw form. Log transformed for inferential analysis to achieve normality.

Table 15

Effect of Nutrition Intervention on Demand in HP-LED Condition for AISB Participants

Demand Metric	*t*-statistic	*Pre-Intervention Mean (SD)*	*Post-Intervention Mean (SD)*
Intensity of Demand	-0.45	14.78 (9.18)	15.54 (9.44)
Alpha	-0.60	.02 (.05)	.05 (.2)
Breakpoint 0	0.71	56.01 (91.27)	39.28 (3.86)
Price Maximum	0.77	86 (119.64)	79.23 (121.17)
Output Maximum	0.82	72.32 (96.17)	57.35 (91.02)

Note. Values presented in raw form. Log transformed for inferential analysis to achieve normality.

Table 16

Effect of Nutrition Intervention for AISB Participants with High Levels of Participation

Demand Metric	*H*-statistic	*Pre-Intervention Mean (SD)*	*Post-Intervention Mean (SD)*
Intensity of Demand	3.231	11.734 (9.14)	16.85 (8.80)
Alpha	1.097	.04 (.07)	.11 (.33)
Breakpoint 0	.109	29.36 (71.74)	32.87 (76.79)
Price Maximum	.234	4.57 (4.66)	5.92 (10.47)
Output Maximum	.005	22.51 (37.26)	28.69 (40.04)

Note. For all comparisons, *df* = 1.

Table 17

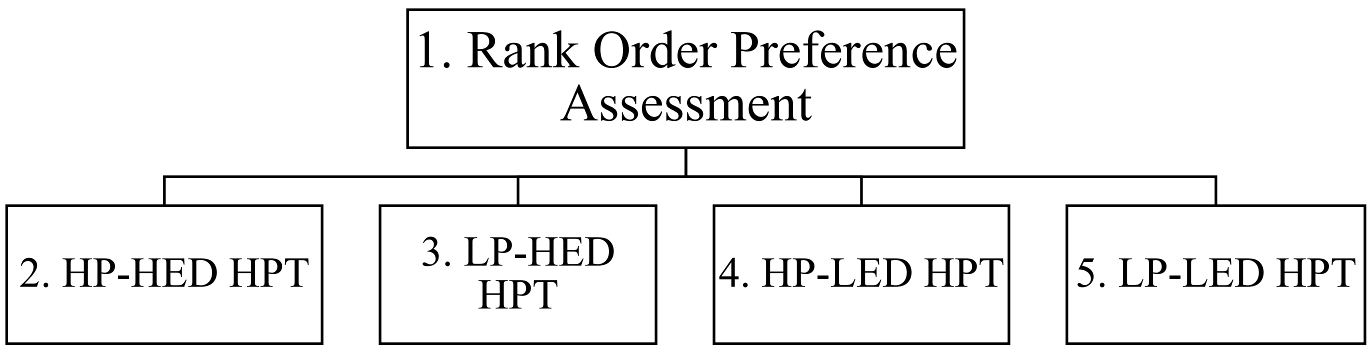
Effect of Nutrition Intervention on Demand in Internet Purchasing Task for AISB Participants

Demand Metric	*t*-statistic	*Pre-Intervention Mean (SD)*	*Post-Intervention Mean (SD)*
Intensity of Demand	-1.05	4.73 (0.97)	4.94 (0.24)
Alpha	0.09	0.15 (0.5)	0.11 (0.3)
Breakpoint 0	-0.24	18.25 (9.92)	18.79 (9.3)
Price Maximum	0.90	6.70 (3.9)	5.5 (3.9)
Output Maximum	0.08	22.40 (18.21)	17.96 (14.89)

Note. Values presented in raw form. Log transformed for inferential analysis to achieve normality.

Figure 1

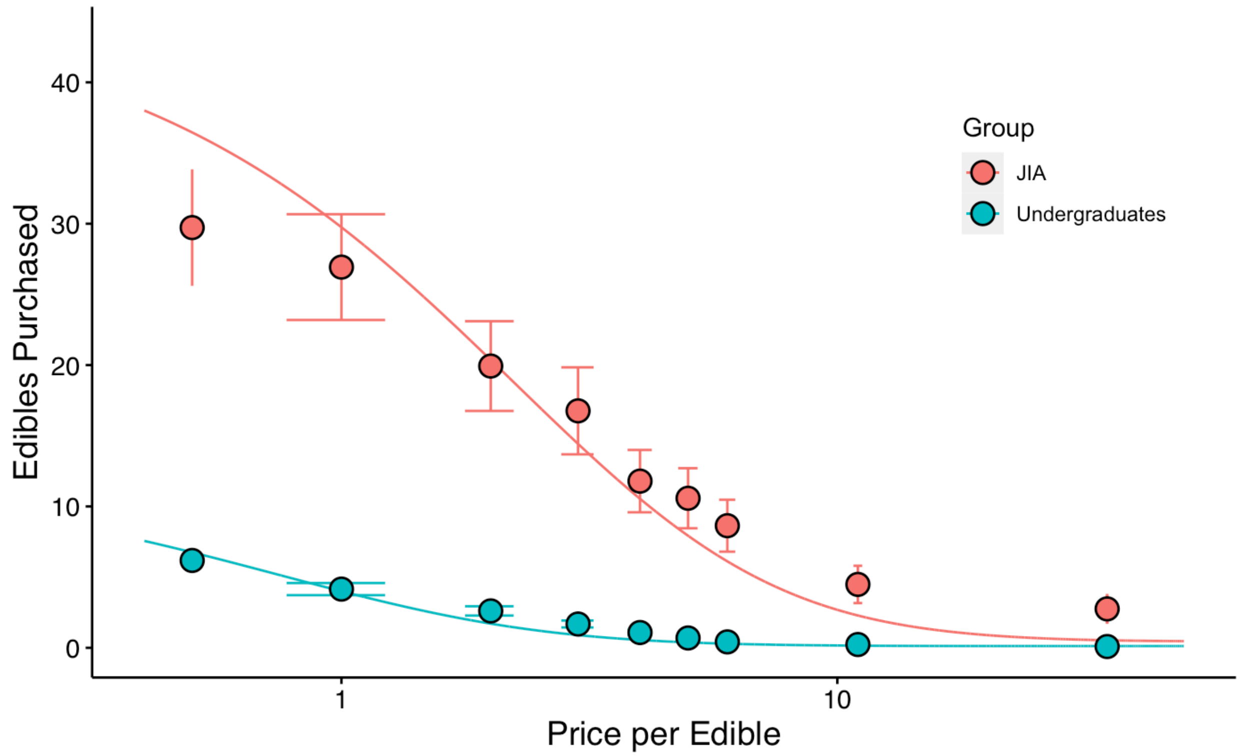
Order of Assessments for Experiment 1



Note. HPT = Hypothetical Purchasing Task

Figure 2

Between-Groups Comparison of Demand in the HP-HED HPT Condition in Experiment I

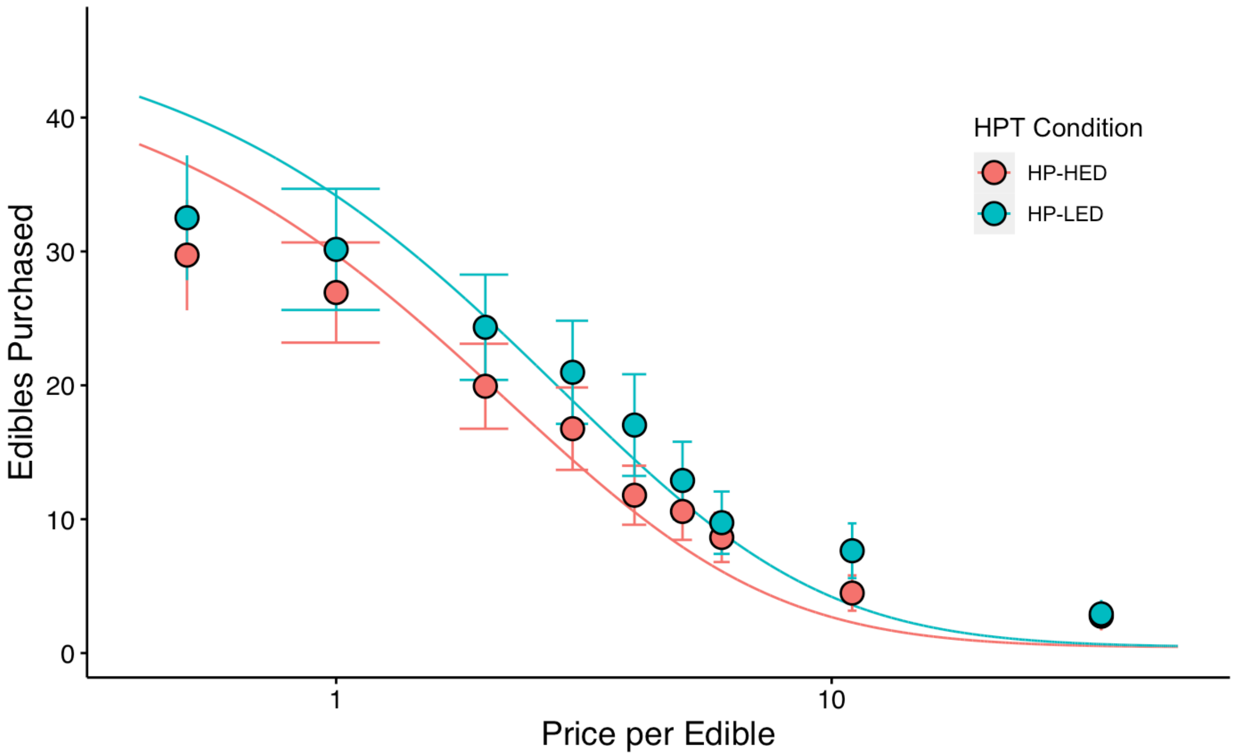


Note. Graph includes data for the undergraduate group (n = 108) and the JIA group (n = 64).

Bars represent standard error of the mean.

Figure 3

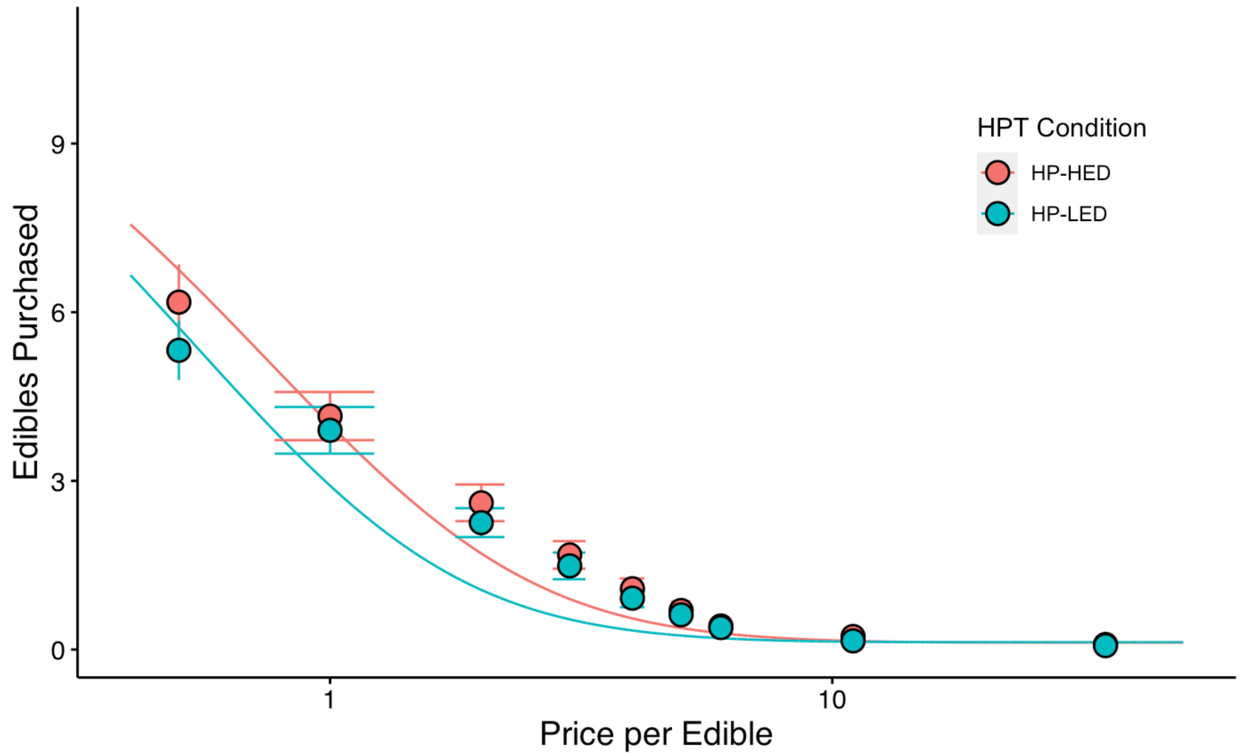
Comparison of Demand Across HPT Conditions for the JIA Group



Note. Graph includes data for the JIA group (n = 64) only. Bars represent standard error of the mean.

Figure 4

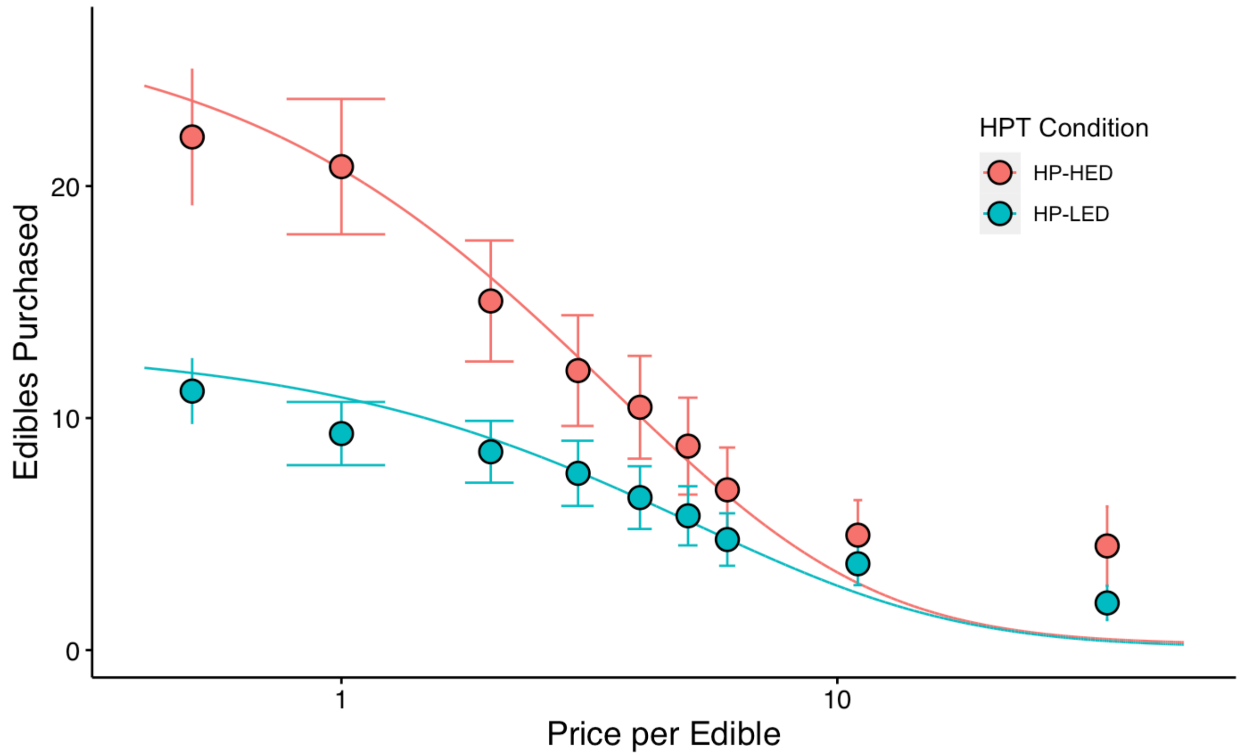
Comparison of Demand Across HPT Conditions for the Undergraduate Group



Note. Graph includes data for the undergraduate group (n = 108) only. Bars represent standard error of the mean.

Figure 5

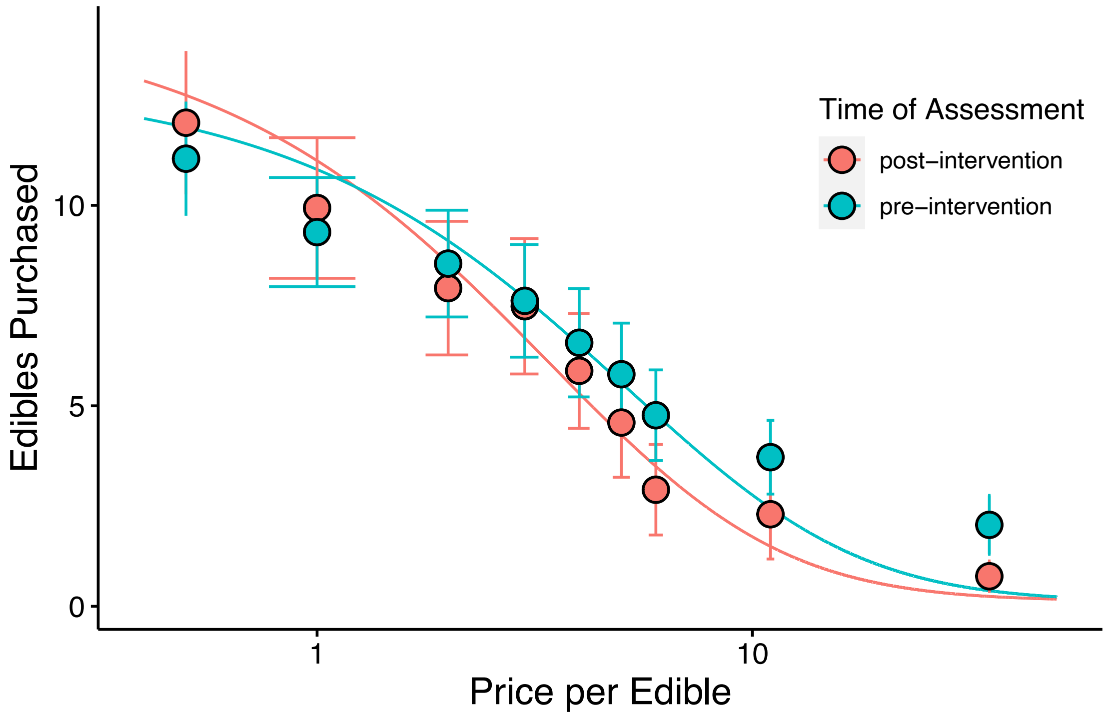
Comparison of Demand Across HPT Conditions for the AISB Group



Note. Bars represent standard error of the mean.

Figure 6

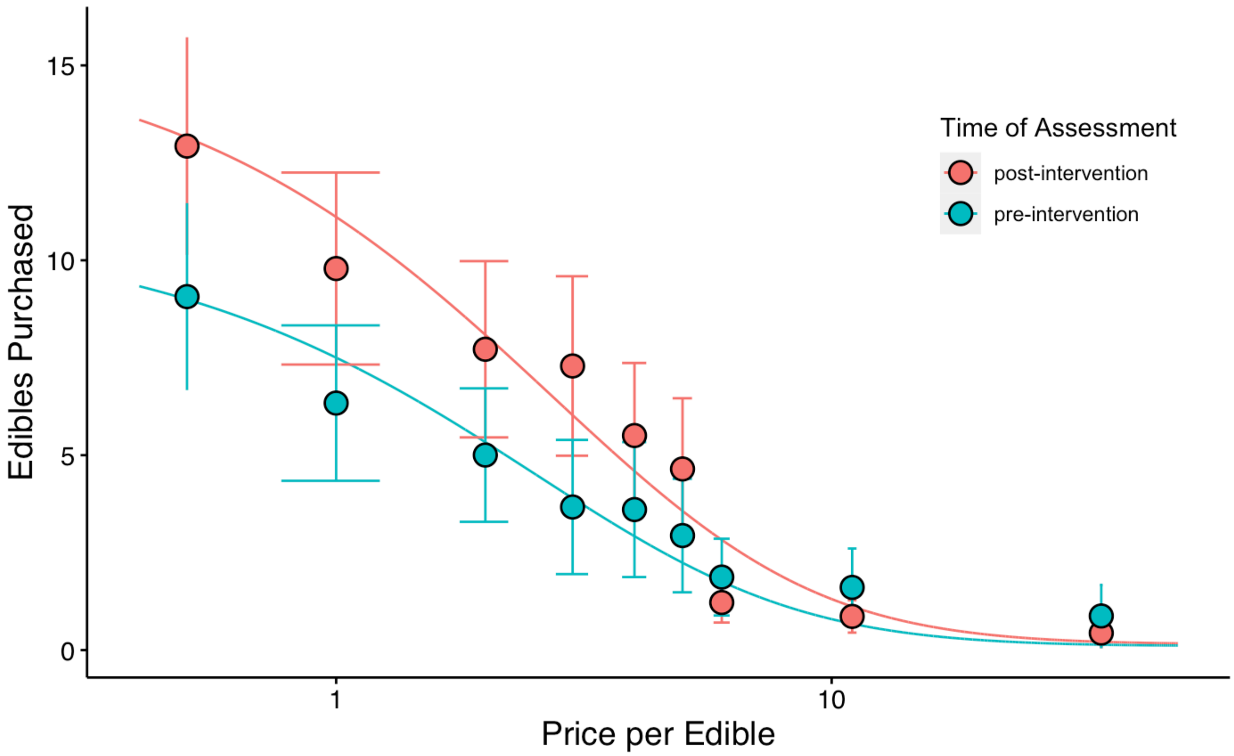
Effect of Nutrition Intervention on Demand in the HP-LED HPT Condition



Note. Graph includes data for the AISB group pre-intervention (n = 42) and post-intervention (n = 31). Bars represent standard error of the mean.

Figure 7

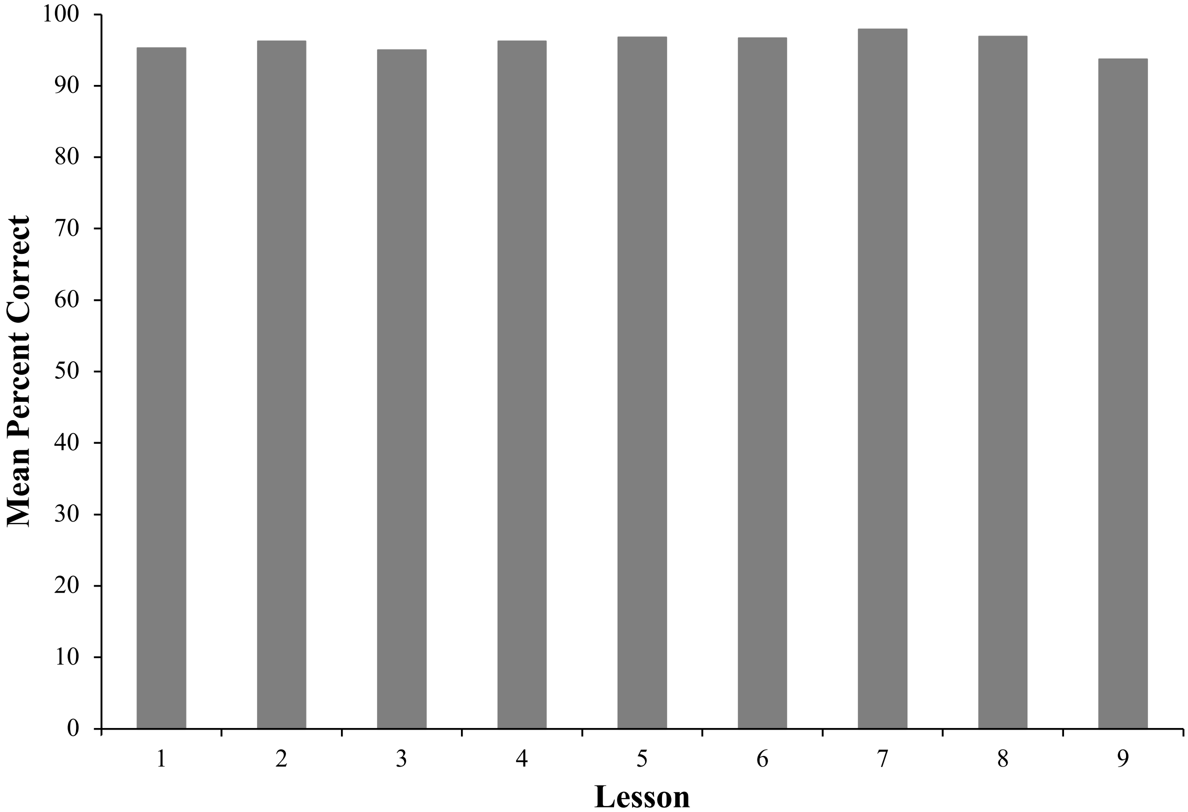
Effect of Nutrition Intervention on Demand for Participants with High Levels of Participation



Note. Graph includes data for participants in the AISB with high levels of participation pre-intervention (n = 15) and post-intervention (n = 13) in the high preferred low energy density hypothetical purchasing task condition. Bars represent standard error of the mean.

Figure 8

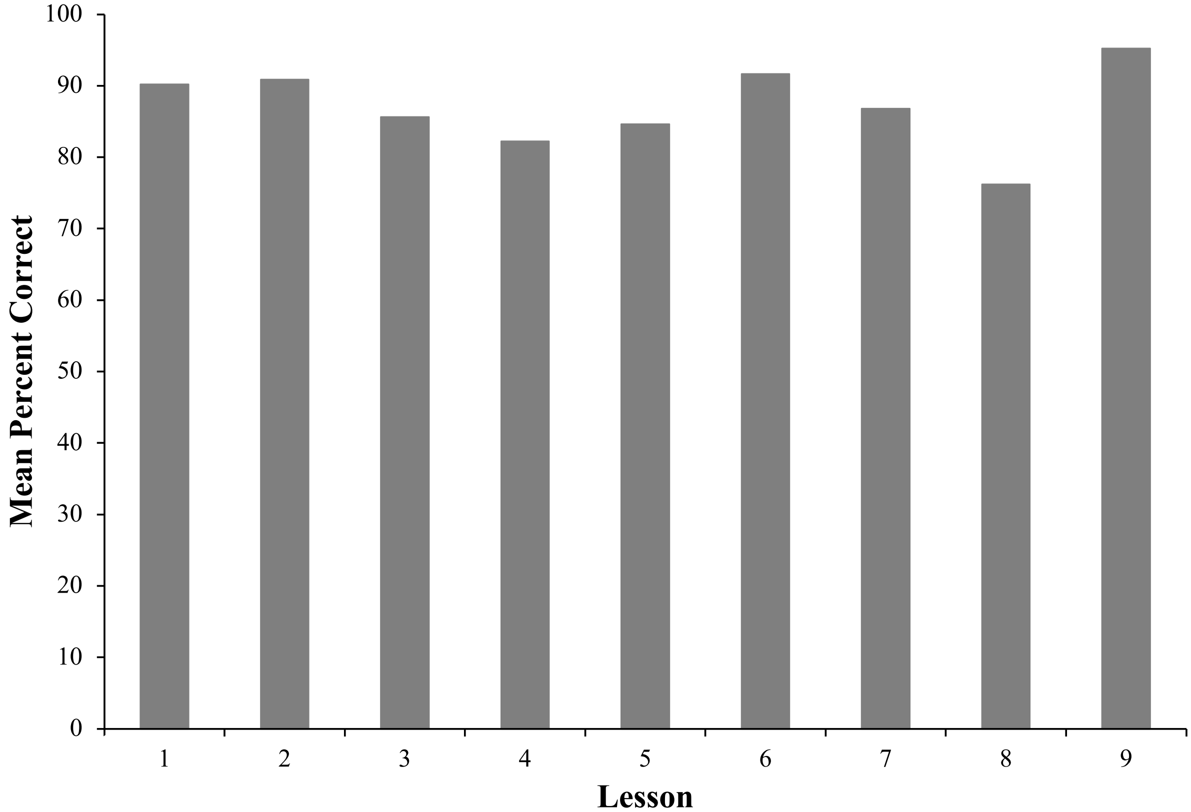
Mean Percentage of Correct Responding for Guided Notes Across Lessons in Experiment II



Note. Data did not indicate remedial lessons were required for any lesson (i.e., mean scores were ≥70% across all lessons).

Figure 9

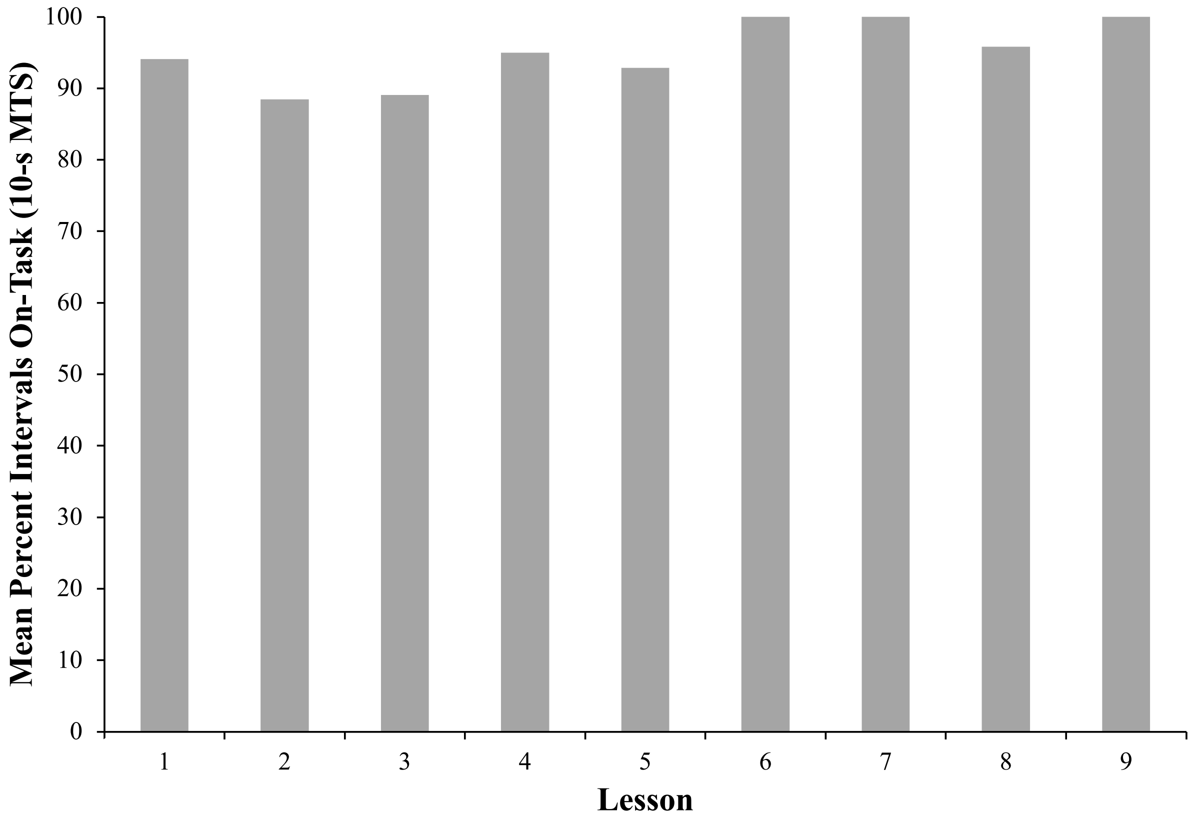
Mean Percentage of Correct Responding for Interteaching Across Lessons in Experiment II



Note. Data did not indicate remedial lessons were required for any lesson (i.e., mean scores were ≥70% across all lessons).

Figure 10

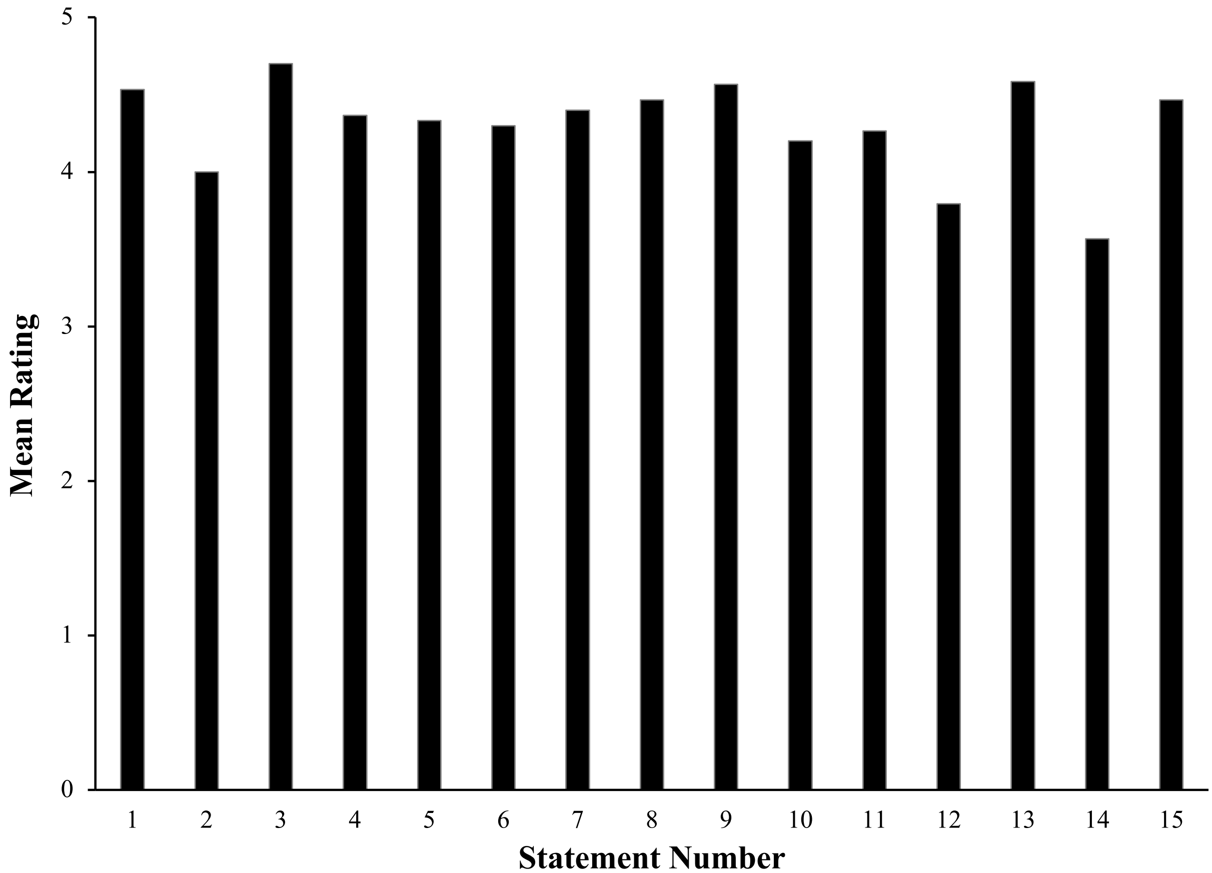
Mean Percentage of Intervals On-Task Across Lessons in Experiment II



Note. MTS = momentary time sampling

Figure 11

Mean Rating Across Statements for Social Validity Responses



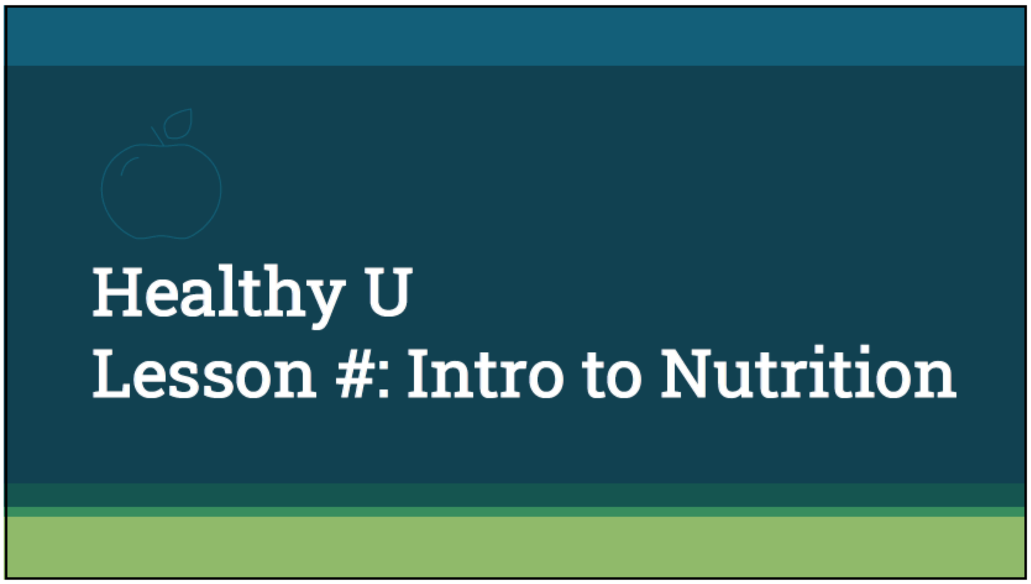
Note. Social validity data were collected anonymously and completing the questionnaire was voluntary. $n = 30$.

Appendix A

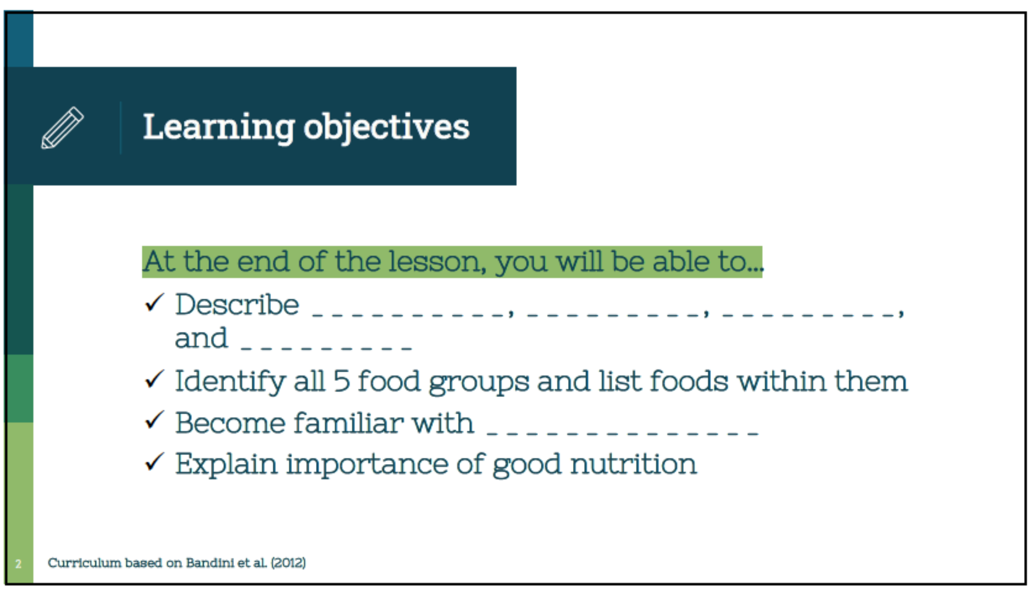
Sample Printed Instructional Materials

Sample Guided Notes

Name:______________________________ Date:___________________________



1



2

Sample Interteaching Worksheet

Name:______________________________________ Date:_______________________

Healthy U Interteaching
Lesson 1: Intro to Nutrition

Rules for Interteaching

1. Use an inside voice
2. Stay in your seat
3. Only one person speaks at a time
4. Work together as a team!

Instructions: In peer groups, take turns answering the question for your peers. One person should be the "peer teacher," who explains the answer. The other students should be "peer students," who listen to the peer teacher and confirm or correct the explanation.

Write your answers using complete sentences in the space provided below.

1. What is nutrition?

2. Why is it important to learn about nutrition?

3. What are the five foods groups? List foods in each group.

4. How is food similar to fuel in a car?

Sample Class Activity Worksheet

Name:____________________________ Date:_______________________

Lesson 2 Class Activity: Local Menu Activity

Instructions: Complete the worksheet using information from the restaurant menu. *Complete the first part with the instructor.*

Restaurant #1:____

1. Which menu item would you select for lunch or dinner (including sides and beverage)?

____

2. List all of the foods in this meal:

____

3. Categorize each of the foods in this meal by food group. If the meal does not contain food from a food group, write “none” under that food group.

Protein	Grain	Fruit	Vegetable	Dairy

4. Which food group(s) is/are missing from the meal?

____

5. What side item could you add or substitute to include one food from each food group in your meal? (Must be a side item from the menu)

____

Complete the next section on your own. Raise your hand if you need help.
Restaurant #2:____

1. Which menu item would you select for lunch or dinner (including sides and beverage)?

____

2. List all of the foods in this meal:

Appendix B

Adapted Social Validity Questionnaire

Healthy U Social Validity Questionnaire

Purpose: We really enjoyed working with you throughout Healthy U! We hope you enjoyed your experience as well. We need your input to improve future courses taught by the ABA Team at Mt. Meigs.

Instructions: Please circle a number from 1-5 for each statement. Circling a 1 indicates that you strongly disagree with the statement and circling a 5 indicates that you strongly agree with the statement. If you circle a 1 or 2, please let us know why in the blank blanks provided below. Thank you for your time and input!

	Strongly Disagree	Disagree	Neither agree nor disagree	Agree	Strongly Agree
1. I enjoyed the health U Program and I would recommend it to other residents at Mt. Meigs.	1	2	3	4	5
2. The topics were relevant to my own nutritional needs.	1	2	3	4	5
3. The course was organized and easy to follow along with.	1	2	3	4	5
4. The instructor encouraged participation and interaction.	1	2	3	4	5
5. The course content was engaging and understandable.	1	2	3	4	5
6. The instructor was prompt and reliable.	1	2	3	4	5
7. The instructor was knowledgeable about topics covered.	1	2	3	4	5
8. The instructor was approachable.	1	2	3	4	5
9. The instructor worked well with participants.	1	2	3	4	5
10. Meeting 1-2 times per week for 9-10 weeks worked for my dorm.	1	2	3	4	5
11. Meeting for 1-2 hours each session worked for my dorm.	1	2	3	4	5
12. I have made noticeable lifestyle changes since participating in Healthy U.	1	2	3	4	5
13. I enjoyed attending Healthy U sessions.	1	2	3	4	5
14. I discussed topics covered in Healthy U with peers and staff throughout the week, when I wasn't in a Healthy U session.	1	2	3	4	5
15. I would consider assisting with Healthy U in the future.	1	2	3	4	5

Other ideas/reasons for a "1" or "2" above/support for items above:

____
____
____
____
____
____
____
____
____
____
____
____

Adapted from Lauria (2018)