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Choices Between Money and Hyper-Palatable Food: Choice Impulsivity and Eating Behavior

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Abstract

Objective: Choice impulsivity may influence eating behavior. The study tested whether choice impulsivity, termed delay discounting, may be related to food generally, or may be specific to hyper-palatable foods (HPF). The study also determined whether a discounting task with choices between money and food may have utility in predicting obesity-related outcomes.

Method: Participants ($N = 284$) completed a task that assessed choices between smaller reward available immediately and larger reward available later. Single commodity conditions presented choices between amounts of HPF, non-HPF, or money (e.g., HPF now vs. HPF later). Cross-commodity conditions presented choices between money and food commodities (e.g., money now vs. HPF later; money now vs. non-HPF later).

Results: There were no significant differences in discounting of HPF and non-HPF in single commodity conditions (Mean ln[k] difference = .40, $p = .058$). In the cross-commodity conditions holding money constant as the immediate reward, individuals discounted HPF significantly less than non-HPF (Mean ln[k] difference = .92; $p = .0001$). In regression analyses, individuals with excess HPF intake, greater HPF craving, and higher BMIs were more likely to choose HPF immediately, when money was the delayed reward (p values = .003 to .008).

Conclusions: Choice impulsivity may be specific to foods that are hyper-palatable. Results suggest that individuals with excess HPF intake, higher HPF craving, and higher BMIs may

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exhibit a general tendency toward impulsive decision making that may be exacerbated in an obesogenic environment that provides wide access to HPF.

Keywords

behavioral economics; body mass index; craving; cross-commodity; food choice

Obesity is a major public health problem. In the United States, more than 40% of adults have obesity (body mass index [BMI] ≥ 30 kg/m^2; Centers for Disease Control and Prevention, 2020). Obesity is largely driven by obesogenic food environments, in which palatable foods are widely available, easily accessible, and highly rewarding to consume (Roberto et al., 2015; Swinburn et al., 2011). However, considering that more than half of the U.S. population does not have obesity, evidence suggests that individual-level factors may moderate the degree to which an obesogenic food environment may elevate an individual's obesity risk (Gunstad et al., 2020). Thus, it is important to identify individual-level risk factors to inform prevention efforts.

One characteristic that may influence individual-level eating behavior and downstream obesity risk may be choice impulsivity, here formally referred to as delay discounting (Bickel & Marsch, 2001). Individuals high in delay discounting exhibit a strong preference for small, immediate reward over larger, delayed reward. In an obesogenic environment, individuals high in delay discounting may exhibit a strong preference for the immediate reward of palatable foods, at the expense of a larger future reward, such as a healthy BMI (DeHart et al., 2020; Epstein et al., 2010). Delay discounting is measured by asking participants a series of questions regarding whether they would prefer to receive a smaller reward now, or a larger reward later (e.g., $5 now vs. $50 in 1 month). Delay discounting tasks most commonly use hypothetical money as the incentive, because money has explicit value and thus facilitates comparisons across individuals.

Delay discounting is considered a transdiagnostic construct consistently associated with behavior that may be immediately rewarding but presents risks to long term health such as substance use, gambling, and risky sexual behavior (Bickel et al., 2012, 2019). However, despite its robustness for predicting health risk behaviors, findings in the literature regarding the association between delay discounting and obesity have been mixed. For example, two recent systematic reviews found that approximately half of studies they reviewed reported positive, significant associations between discounting and BMI/obesity outcomes (Barlow et al., 2016; Tang et al., 2019). The source of the observed discrepancy in findings may be at least partially attributable to study methodology. Specifically, whereas most discounting studies use money as a commodity, palatable food may be a more ecologically relevant commodity for studying discounting as related to obesity. In this regard, a review comparing discounting studies using money or palatable food indicated that studies using money generally reported null findings whereas studies using palatable food generally found positive associations with obesity-related outcomes (Barlow et al., 2016). Thus, using a commodity specific to palatable food may have greater predictive utility for obesity-related outcomes compared with monetary incentives.

Although palatable food may have greater relevance for obesity-related outcomes compared with other commodities, there have been several major limitations in prior studies that used food in discounting tasks. First, prior studies in the literature have focused on palatable foods that may be highly rewarding to consume; however, they lacked a robust rationale for the specific foods used in the tasks, resulting in a high degree of variability in foods used across studies. In addition, no prior studies have included both palatable and comparator foods that were not highly palatable. It is therefore unclear whether choice impulsivity may be generally related to food or more specifically to palatable, highly rewarding foods.

In addition to the aforementioned limitations, another limitation of prior research is that the discounting tasks may not be reflective of real-world choices, which may limit the ecological validity of the tasks. For example, most prior studies compared a small amount of palatable food available now versus a larger amount of palatable food available later. However, in an obesogenic food environment in which palatable foods are almost always available, individuals are not commonly faced with decisions between a small amount of palatable food now (e.g., one piece of pizza now) versus a larger amount of palatable food later (e.g., eight slices of pizza tomorrow). Instead, it may be more likely that people encounter choices between palatable food and money (e.g., one slice of pizza now vs. $5 tomorrow). Thus, cross-commodity comparisons of palatable foods and money may hold greater utility in understanding variability in choice impulsivity related to palatable foods, and the impact of such decision-making processes on dietary intake, motivation to consume palatable foods (e.g., food craving), and obesity. To our knowledge, only one prior study examined cross-commodity discounting of money and palatable food among individuals who had obesity; however, the study comprised entirely individuals with obesity and thus variability in discounting across the full BMI range could not be examined (Mellis et al., 2018).

The purpose of the current study was twofold. The first aim was to determine whether there were differences in discounting of hyper-palatable foods (HPF), which have artificially enhanced palatability and are highly rewarding to consume, relative to foods that are not hyper-palatable. Single commodity tasks were used to test differences in discounting of HPF (HPF now vs. HPF later) compared with non-HPF (non-HPF now vs. non-HPF later). Additionally, a cross-commodity task was used to test differences in discounting of HPF relative to non-HPF while holding money constant as an immediate reward (e.g., money vs. HPF; money vs. non-HPF). HPF were selected using the definition by Fazzino et al. (2019), which identifies HPF from combinations of nutrients present at thresholds that may induce hyper-palatability (Fazzino et al., 2019). The second aim was to determine whether a cross-commodity discounting task with comparisons between HPF, non-HPF, and money had greater utility in examining outcomes related to obesity, compared with single commodity discounting tasks with HPF, non-HPF, or money. Outcomes of interest were excess dietary intake of HPF, which is a well-documented risk for obesity (Drewnowski, 1998; Leigh et al., 2018), craving for HPF, which represents an enhanced motivational state to consume HPF and has been strongly implicated in weight gain and obesity (Boswell & Kober, 2016), and BMI. We hypothesized that HPF would be discounted differently than non-HPF (Aim 1), and that cross-commodity discounting conditions would be more strongly associated with the obesity-related outcomes than single commodity conditions (Aim 2).

Method

Procedures

Participants were recruited through the Amazon Mechanical Turk (MTurk) online platform. To reach potential participants with varying availability owing to work and/or personal schedules, study surveys were released in six batches on varying weekday and weekend times. The study target sample was $N = 300$ adults residing in the United States, to correspond with study measures that used U.S. foods/food formulations. Thus, eligibility criteria consisted of adults 18–65 years old residing in the United States. In addition, to increase the likelihood of obtaining high quality data, participants were required to have an MTurk task approval rate of ≥99% and to have completed ≥1,000 studies on MTurk (Peer et al., 2014). Eligible individuals were automatically identified by Mturk and presented with the study listing. Individuals who provided informed consent to participate were subsequently presented with an automated delay discounting task consisting of single and cross-commodity conditions (detailed in measures section below). Following completion of the discounting task, participants completed surveys that inquired about eating behavior and food preferences. The study took approximately 60–90 minutes to complete. Participants received $4.50 for completing the study, which is consistent with compensation rates for Mturk studies in behavioral sciences (Chandler & Shapiro, 2016; Mellis & Bickel, 2020). The study was granted ethical approval by the University of Kansas Institutional Review Board.

Measures

Delay Discounting—The computer-based adjusting amount task consisted of single and cross-commodity conditions that included commodities of money, HPF, and/or non-HPF. We first describe the commodities used in the task, followed by the task itself.

HPF and Non-HPF Commodities.: HPF and non-HPF food commodities were identified using the quantitative definition of HPF (Fazzino et al., 2019). Specifically, foods were identified as HPF if they meet criteria for one or more of the following groups: (a)fat and sodium HPF (>25% kcal from fat and ≥.30% sodium); (b) fat and sugar (>20% kcal fat and >20% kcal sugar); and (c) carbohydrates and sodium (≥40% carbohydrates and ≥.20% sodium; Fazzino et al., 2019). To identify HPF items for the discounting task, the HPF definition was applied to the Food and Nutrient Database for Dietary Studies (FNDDS), a database from the U.S. Department of Agriculture that is considered representative of the U.S. food system (USDA Agricultural Research Service, 2018). Twenty-four commonly consumed foods were selected from the FNDDS for inclusion according to their status as HPF ($n = 12$) or non-HPF ($n = 12$). Foods included in the study are displayed in Supplemental Table S1. Foods were presented to participants in units of a standard U.S. serving size (U.S. Food and Drug Administration, Center Food Safety and Applied Nutrition, 2018; USDA Agricultural Research Service, 2018).

Before the task, participants were provided with the list of 12 HPF options, followed by the list of 12 non-HPF options, and were instructed as follows: “From the list below, please choose the food you would prefer to eat now.” Participants’ most preferred food item from the HPF and non-HPF list were used in the discounting task. Participants were presented with the definition of one serving of their selected food (e.g., one serving = one full size Snickers bar) during each food trial to facilitate their understanding of the food quantity presented in each choice.

Money Commodity.: Money was presented in U.S. dollars in the discounting task. To compare discounting rates across food and money commodities, an exchange rate was set at $2.50 = 1 serving of food. The monetary value aligned with the general market value for one serving of each food used in this study.

Delay Discounting Task.: Before the task, participants read the following instructions:

> In this task you will be presented with two options to choose from. The options will be either an amount of money or number of servings of food. One of the options will be available now and the other will be available in the future. For each set of options, please indicate which option you would prefer. Each serving of food is worth $2.50. Please answer as if these options were available to you in your current everyday life. Assume you can save the food for later.

In each trial of the discounting task, participants indicated their preferred choice for either a smaller reward available immediately or a larger delayed reward. Specifically, participants were asked: “Would you prefer [commodity] now or [commodity] in [delay]?” and indicated their preferred choice with a mouse click. Depending on the participants’ selection of the immediate or delayed reward in each trial, the next immediate reward was adjusted up or down by 50% of the prior adjustment (Frye et al., 2016). Within each condition, five delay periods (1 day, 1 week, 1 month, 6 months, 1 year) were presented to participants, and their responses over 6 trials were used to determine their indifference point for each delay. To minimize the potential for ordering effects, participants were randomly assigned to be presented with conditions in one of four possible orders.

The computer-based adjusting amount task consisted of all possible combinations of immediate and delayed hypothetical money, HPF, and non-HPF (i.e., both single and cross-commodity). Table 1 presents the discounting conditions presented in the task. The single commodity tasks conditions consisted of the following three conditions: (a) HPF now versus HPF later; (b) non-HPF now versus non-HPF later; and (c) money now versus money later. Cross-commodity conditions consisted of all permutations ($n = 6$) across money, HPF, and non-HPF (see Table 1). Participants completed each condition twice, once for commodity amounts that were small in magnitude: $10 or four servings of food ($2.50 per serving × 4 servings = $10 equivalent in food) and a second time for amounts large in magnitude: $100 or 40 servings of food ($2.50 per serving × 40 servings = $100 equivalent in food). The two aforementioned magnitude conditions were used to test whether a delayed reward that was large in magnitude ($100) was discounted less steeply than a delayed reward with a smaller magnitude ($10), to determine the magnitude effect (Green et al., 1981, Green et al., 1997). In total, the discounting conditions consisted of six single-commodity conditions and 12 cross-commodity conditions (18 conditions total), and 540 trials.

Demographics and Hunger—Participants provided the following demographic information: age, race/ethnicity, sex, household income, employment status, and highest level of education, and also reported their height and weight. Participants were asked to rate their current hunger level using a 100-mm visual analog scale (VAS) (0 = *not hungry at all*, 100 = *very hungry*), as has been done previously (Hendrickson & Rasmussen, 2013; Robertson & Rasmussen, 2018).

Hyper-Palatable Food Intake—The Dietary History Questionnaire (DHQ) is a well-established questionnaire designed to measure the frequency at which individuals consumed various types of foods over a specified period of time (National Institutes of Health, Applied Research Program, National Cancer Institute, 2007, 2018). A modified version of the DHQ was used in the current study to measure HPF consumption in the past two weeks. Ten categorical response options assessed HPF intake from 0 times in two weeks to 6+ times per day, as follows: 0 times in the past two weeks; 1 time in the past two weeks; 2–3 times in the past two weeks; 1–2 times per week; 3–4 times per week; 5–6 times per week; 1 time per day; 2–3 times per day; 4–5 times per day; 6 or more times per day. The DHQ has established convergent validity with similar measures of food intake (Subar et al., 2001) and performs slightly better than similar measures when estimating frequency of intake of palatable foods (Thompson et al., 2002). In total, seven questions inquired about consumption of the following types of HPF: (a) sweets and baked goods; (b) meats and fish-based foods (e.g., bacon; fish sticks); (c) breads and breakfast foods; (d) refined grain-based items; (e) potato-based items; (f) salty snacks; and (g) toppings (e.g., peanut butter). For analyses, a dichotomous variable was created to identify excess dietary intake of HPF (excess intake vs. not). Excess HPF intake was operationalized as consumption of HPF more than once daily. The choice was supported by the structure of our data, in which the majority of individuals (63%) endorsed consumption of at least one type of HPF daily, whereas 37% endorsed consumption of at least one type of HPF 2–6+ times per day. Our prior work revealed that >60% of foods in the US food system were HPF (Fazzino et al., 2019); thus it is plausible that U.S. adults may regularly encounter and consume one HPF on a daily basis, even if attempting to limit unhealthy food intake.

Craving—Craving for HFP was measured using the Food Craving Inventory (FCI; White et al., 2002) which investigates the frequency of craving for fast foods, carbohydrates/starches, sweets, and high-fat foods over the past month. The FCI has demonstrated acceptable content and concurrent validity when compared with similar measures and constructs (White et al., 2002) and good test–retest reliability (Chao et al., 2014; White et al., 2002). Previous research has demonstrated that craving of foods high in fat, sugar, or starch, and fast foods may be associated with weight gain (Chao et al., 2014).

Data Analysis

Analyses were conducted in R statistical software using the nlmrt package (Nash, 2016; R Development Core Team, 2012). Data from the discounting task were used to estimate discounting rates for each participant within each commodity condition and fit k (Mazur, 1987). The value of k represents the estimated rate at which the delayed commodity loses subjective value over a time delay. High k values indicate rapid discounting and suggest a tendency to choose a smaller, immediately available commodity over a larger delayed commodity. The estimated k values in the current study were normalized using natural logarithm transformation to address positive skewness, which is typical of discounting rates. The transformed $\ln(k)$ values were then used in subsequent correlational and primary regression analyses. In addition, an alternative atheoretical index of discounting, Area under the curve (AUC) was also calculated for use in parallel, supplemental analyses (Myerson et al., 2001). Specifically, $\mathrm{AUC}log\ d$ was used for analyses, which contains a transformation to address the imbalanced contribution of different indifference points to the total AUC value (Borges et al., 2016).

Pearson correlation analysis was used to test correlations among discounting ($\ln[k]$) values between the nine conditions for each respective magnitude. In addition, a two-way repeated-measures analysis of variance (ANOVA) tested differences in discounting between small and large magnitudes for single commodity conditions (money, HPF, and non-HPF).

To test the study hypotheses, a second repeated-measures ANOVA model and regression models were constructed. Models were constructed to include relevant single and cross-commodity discounting conditions germane to specific research questions. More specifically, to test whether individuals discounted HPF differently than non-HPF (Aim 1), a two way repeated-measures ANOVA was constructed to test differences in mean $\ln(k)$ values for type of condition (single or cross-commodity) and for conditions in which food was offered at a delay (HPF or non-HPF). Simple effects comparisons were conducted for the single commodity conditions for HPF and non-HPF (HPF now vs. HPF later; non-HPF now vs. non-HPF later), to determine whether HPF was discounted differently than non-HPF in the single commodity conditions. Simple effects comparisons with cross-commodity conditions were conducted with conditions in which HPF or non-HPF was delayed, and money was the immediate reward (money now vs. HPF later; money now vs. non-HPF later), to determine whether ln(k) values significantly differed between HPF and non-HPF when money was held constant as the immediate reward. Thus, the analyses facilitated an examination of whether HPF was discounted differently than non-HPF using summary level data averaged across groups (e.g., the aforementioned conditions with delayed HFP vs. conditions with delayed non-HPF), as well as key individual contrasts for single and cross-commodity effects.

To test the utility of cross-commodity tasks in examining obesity-related outcomes relative to single commodity tasks (Aim 2), a series of regression models were constructed to model the associations between seven discounting conditions (three single commodity + 4 cross-commodity conditions) and the obesity-related variables of interest. Single commodity conditions were: (a) HPF now versus HPF later; (b) non-HPF now versus non-HPF later; and (c) money now versus money later. Cross-commodity conditions were the following comparisons between HPF and money or non-HPF: (d) money now versus HPF later; (e) HPF now versus money later; (f) HPF now versus non-HPF later; and (g) non-HPF now versus HPF later. To conduct model comparison analyses, each discounting condition was included in its own regression model. Thus, seven logistic regression models were constructed to test the association between each discounting condition and excess dietary intake of HPF as a dichotomous outcome (excess HPF intake/not). Seven multiple linear regression models tested the association between each of the discounting conditions and HPF craving. Finally, seven multiple linear regression models tested whether each of the discounting conditions were associated with BMI. Current hunger level may influence discounting of food (Loeber et al., 2013) and may be associated with BMI (Devoto et al., 2018) and was therefore included as a covariate in analyses with craving and BMI.

Model comparison techniques based on Akaike information criteria (AIC) were used to compare the relative strength of different discounting conditions to predict obesity-related outcomes (Burnham et al., 2011). AIC values index the amount of information lost when predicting a dependent variable, while also penalizing for model complexity. As such, when comparing models, smaller AIC values are preferred and indicate greater accuracy in predicting the values of the dependent variable, relative to larger AIC values. Furthermore, the AIC difference (ΔAIC) between two models predicting the same dataset can be converted into an evidence ratio that quantifies the likelihood that one model (model A) predicts with greater accuracy than another model B; this affords statement such as, "model A is *x* times more likely than model B to predict the dependent variable with greater accuracy." Based on guidelines provided by Burnham et al. (2011), a ΔAIC of 4 served as our threshold for a preferred model.

Visual graphing techniques were used to confirm that assumptions were met for all analytic models. For BMI models, Q-Q plots indicated mild deviations from normality at tail ends. *p* values were adjusted using the Hochberg method to protect against type I error (Hochberg, 1988).

Discounting Magnitudes and AUC Values—All analyses described above were conducted for both the small magnitude and large magnitude conditions. Results for the small magnitude findings are presented in the result section. The findings for the large magnitude condition were similar to the small magnitude condition; thus, the findings for the large magnitude condition are briefly described in the Results section and are reported in detail in the online supplemental materials section. In addition, in parallel with the main analyses using ln (k) values, supplemental analyses were conducted using AUCl*og d* as a measure of discounting. Findings using AUCl*og d* are summarized in the results and reported in detail in the online supplemental materials section.

Missing Data and Data Quality Criteria—Discounting data were evaluated for quality and orderliness using the criteria from Johnson and Bickel (2008) to identify nonsystematic data. We applied the Johnson and Bickel (2008) criteria to the single commodity money data and removed participants from the dataset entirely who violated both criteria for the single commodity money condition. Johnson and Bickel (2008) developed the criteria on data from single commodity discounting studies that used money as the commodity. Furthermore, the criteria have not been validated for cross-commodity studies or commodities other than money. Thus, the criteria were applied to the single commodity money condition, which yielded $n = 12$ participants (4% of study sample) who violated criteria 1 and 2 and were removed from the small magnitude analyses, and $n = 11$ people who were removed from the large magnitude analyses. Thus, results are reported from models that used the final sample ($N = 284$ for small magnitude; $N = 285$ large magnitude).

Of 300 individuals who consented to participate, $N = 284$ (95%) completed all study measures and provided systematic discounting data; thus, missing data were minimal. However, participants who skipped individual survey items were included in analyses for which they provided data. In the small magnitude condition, eight participants skipped item(s) on the DHQ ($n = 5$) or FCI ($n = 3$) and thus were not included in analytic models using the DHQ or FCI data, respectively. Additionally, one participant reported height and weight data that yielded BMI that was not physically plausible and was excluded from analyses with BMI.

Results

Participants

Sample characteristics are displayed in Table 2. The sample comprised 57% females, the majority of the sample (77%) was between ages 25–50, and 73% were White, non-Hispanic. Most participants (>70%) were employed and had at least some college education. Mean BMI in the sample was 26.08 ($SD = 6.48$). Twenty percent of the sample had a BMI representative of obesity (≥30).

Single- and Cross-Commodity Discounting Values and Magnitude Effect

Median indifference points for the sample were plotted as a function of delay with the line of best fit using Mazur's hyperbolic function (Mazur, 1987) and displayed in Figures 1 and 2. Higher ln(k) values indicate steeper discounting of the delayed reward over time and suggest a tendency to choose the smaller immediate reward over the larger delayed reward, relative to lower ln(k) values. The rank ordering of ln(k) values for each discounting condition is summarized herein and provided in detail in Supplemental Table S2. ln(k) values were largest in the money now versus non-HPF later condition ($M = .22$; $SD = 3.16$), suggesting individuals tended to choose money immediately, when non-HPF was the delayed reward. In contrast, ln(k) values were smallest in the non-HPF now versus money later condition ($M = -6.60$; $SD = 3.10$), suggesting that when non-HPF was the immediate reward, individuals tended to wait for the monetary reward. Overall, ln(k) values for cross-commodity conditions were larger when money was available immediately, and smaller when money was delayed (Supplemental Table S2), suggesting that when choosing between money or food, individuals tended to choose money. A similar pattern was present among the large magnitude conditions (Supplemental Table S3).

Pearson correlation analyses indicated a high degree of correlation among ln(k) values across conditions for the small magnitude conditions (presented in Supplemental Table S4) and the large magnitude conditions (Supplemental Table S5). Results of the first ANOVA model indicated a main effect for magnitude, suggesting that across commodities, individuals displayed significantly greater discounting of the small magnitude reward relative to the large magnitude reward (M ln[k] difference = .60; $F(1, 275) = 35.60$, $p < .001$). However, results also indicated a significant interaction effect $F(1.82, 500.51) = 4.88$, $p = .010$. Pairwise comparisons indicated that individuals displayed greater discounting of the small reward relative to the large reward for the money (M ln[k] difference =.91; $t =$

10.5, $p < .001$) and HPF (M ln[k] difference = .60; $t = 3.08$, $p = .002$) commodities, but not for non-HPF ($p = .084$).

Repeated-Measures ANOVA

The two-way repeated-measures ANOVA was conducted to test the effect of condition type (single or cross-commodity) and delayed commodity (HPF or non-HPF) on discounting rate. There was a significant main effect of condition type (M ln[k] difference = 3.85), $F(1, 283) = 124.95$, $p < .001$, suggesting that individuals discounted food less in the single commodity tasks versus cross commodity tasks. The main effect for delayed commodity was not statistically significant (M ln[k] difference = .26, $F(1, 283) = 3.67$, $p = .057$, indicating that across conditions, HPF was not discounted differently than non-HPF. However, there was a significant interaction between condition and commodity type on discounting rate, $F(1, 283) = 24.78$, $p < .001$. Simple effects tests indicated there was no significant difference in ln(k) values between the single commodity condition with HPF (HPF now vs. HPF later) compared with single commodity condition with non-HPF (non-HPF now vs. non-HPF later; M ln[k] difference = .40, $t = 1.91$, $p = .058$). However, for the cross-commodity conditions in which money was the immediate reward, ln(k) values were significantly lower for the delayed commodity of HPF (money now vs. HPF later) compared with non-HPF (money now vs. non-HPF later; M ln[k] difference = .92; $t = 5.64$, $p < .001$, 95% CI [.60, 1.24]), suggesting individuals were more willing to wait for HPF compared with non-HPF when money was held constant as the immediate reward.

Excess HPF Intake

Results of the logistic regression models indicated that ln(k) from the cross-commodity conditions of HPF now versus money later was significantly associated with excess HPF intake (Table 3; Models 1 and 2). For every one unit increase in ln(k) when choosing HPF now over a delayed monetary reward, the odds of having excess HPF intake were 11% greater. There were no significant associations between the other cross-commodity conditions or single commodity conditions and excess HPF intake (see Table 3).

Findings from the model comparisons using AIC values indicated that the HPF now versus money later condition (Model 1) was a more accurate predictor of excess HPF intake relative to the other conditions (Table 3; Model 1). In terms of evidence ratios, the evidence for the HPF now versus money later condition was at least 20 times stronger than the other models for its accuracy in predicting excess HPF intake.

HPF Craving

Results indicated there was a significant association between discounting and HPF craving for the HPF now versus money later condition (Table 4, Model 1), suggesting that individuals with higher HPF craving tended to choose HPF immediately, when money was available later, even when controlling for hunger. For every one unit increase in ln(k) value when choosing HPF now over a delayed monetary reward, HPF craving was .05 units higher. HPF craving was not significantly associated with ln(k) in the other cross-commodity conditions when controlling for hunger (Table 4; Models 2, 4, and 5). Finally, HFP craving was significantly associated with the single commodity discounting condition for money

(Table 4; Model 6) but not the single commodity conditions for HPF (Table 4; Model 3) or non-HPF (Table 4; Model 7).

Model comparisons using AIC are presented in Table 4. The cross-commodity condition of HPF now versus money later (Model 1) had better model fit (8 AIC points lower; evidence of at least 53 times stronger) compared with the other conditions (see Table 4). The findings using AIC comparisons were consistent with findings from the regression models in that the HPF now versus money later condition was significantly associated with craving (see Table 4).

Body Mass Index

Results indicated there was a significant association between ln(k) values for the HPF now versus money later condition and BMI (Table 5; Model 1), but not the other conditions (Table 5; Models 2–7). Findings suggest that individuals with higher BMIs tended to choose HPF when available immediately (compared with money at a delay). For every one unit increase in ln(k) value when choosing HPF now over a delayed monetary reward, BMI was .36 units higher, when controlling for hunger. There were no significant associations with ln(k) values and BMI for conditions in which HPF was available at a delay (Table 5; Models 3–5), suggesting individuals with higher BMIs were not more willing to wait for HPF when available later. In addition, none of the single commodity conditions were significantly associated with BMI (Table 5; Models 3, 6–7).

Model fit comparisons using AIC values indicated that the cross-commodity condition of HPF now versus money later (Model 1; Table 5) had a substantially lower AIC than the other conditions (≥42 AIC points lower). Thus, the AIC data corroborates frequentist p values in suggesting that the HPF now versus money later condition was an important predictor of BMI, and its predictions of ln(k) values were approximately 1.31×10^9 times more likely than the other models to accurately predict the ln(k) values.

Large Magnitude Analyses

Findings from the large magnitude analyses are summarized here and presented in detail in the online supplemental materials section. Results from the repeated-measures ANOVA with the large magnitude conditions were similar to findings from the small magnitude conditions in which there was a significant interaction between condition type (single or cross-commodity) and delayed commodity (HPF or non-HPF; online supplemental materials). In line with the findings of the small magnitude analyses, simple effects comparisons indicated that there were no significant differences in ln(k) values for single commodity comparisons of HPF versus non-HPF (online supplemental materials). However, there were significant differences in ln(k) values for cross-commodity tasks with money held constant as an immediate reward (online supplemental materials). In regression analyses, there were significant associations between ln(k) values for the HPF now versus money later condition with outcomes for HPF craving and BMI, consistent with the small magnitude analyses (Supplemental Tables S8 and S9). However, there were no significant associations between ln(k) values and excess HPF intake (Supplemental Table S7).

Results using AUC*log d* paralleled the results with ln(*k*) and are reported in detail in the Supplemental Materials (Supplemental Tables S10-S12).

Discussion

Choice impulsivity with food may influence eating behavior. However, it remains unclear whether choice impulsivity may be related to food more generally or may be specific to hyper-palatable foods. The present study was designed to test whether individuals discount the value of HPF differently than non-HPF, and whether cross-commodity discounting of HPF, non-HPF, and/or money may be associated with excess HPF intake, HPF craving, and BMI. The discounting task included standard, single commodity comparisons (e.g., HPF now vs. HPF later), as well as cross-commodity comparisons that reflected real-world decisions between money and food typically encountered in an obesogenic environment. A primary finding was that individuals discounted HPF differently than non-HPF, which was revealed through the cross-commodity comparisons, but was not detected in the single commodity comparisons. Cross-commodity analyses indicated that individuals were more willing to wait for HPF relative to non-HPF (when money was held constant as the immediate reward), likely because HPF have more subjective value compared with non-HPF. Overall, results also indicated that cross-commodity conditions had greater utility in predicting obesity-related outcomes when compared with single commodity conditions. Specifically, cross-commodity conditions with money as the comparison were significantly associated with excess HPF intake, HPF craving, and BMI, and overall had better fit to the data compared with single commodity tasks. Thus overall, findings indicated that choice impulsivity may be specific to HPF, and that using a cross-commodity discounting task comparing money and HPF may have utility in predicting obesity-related outcomes.

The current study provides initial evidence that choice impulsivity may be specific to foods that are highly rewarding to eat. Although this premise has been posited in the literature and has been an underlying assumption of prior discounting work with food (Barlow et al., 2016; Story et al., 2014), no prior study has specifically tested this premise by including non–hyper-palatable foods as a comparison condition. Furthermore, the study findings provide strong evidence for differences in discounting of HPF compared with non-HPF that were revealed in the cross-commodity task, and that were not apparent with the single commodity task. Single commodity tasks (e.g., HPF now vs. HPF later) are limited conceptually as they are unable to distinguish whether responding on a task is driven by an individual's preference for one option (e.g., two slices of pizza now) or a dispreference for the other option (e.g., 12 slices of pizza in one month; Pritschmann et al., 2021). Thus, other factors may at least partially explain the discounting effects observed in single commodity tasks (Pritschmann et al., 2021). In contrast, cross-commodity tasks are able to distinguish preference for a commodity (e.g., HPF) relative to another commodity (non-HPF) when comparing across conditions with parallel designs. For example, we compared two conditions that held the same monetary commodity constant as a reward (money now vs. HPF later; money now vs. non-HPF later), which facilitated a direct evaluation of individuals' preference for HPF available at a delay relative to non-HPF available at a delay. The cross-commodity task thus revealed that individuals discounted HPF to a lower extent compared with non-HPF, indicating a relative preference for delayed HPF compared with delayed non-HPF, when preference was evaluated under directly comparable conditions.

The findings of the current study indicate that using a cross-commodity discounting task with choices between money and food may also have utility for understanding variability in obesity-related outcomes. Specifically, the cross-commodity condition of HPF now versus money later was consistently associated with all outcomes of interest: excess HPF intake, HPF craving, and BMI. Findings using model comparisons with AIC also supported the utility of the HPF now versus money later condition, which fit the data better than most of the other discounting conditions for all outcomes. In contrast, the other single and cross-commodity conditions were not consistently associated with the three outcomes of interest and overall had poorer fit to the data than the HPF now versus money later condition. Thus, findings suggest that a pattern of choosing HPF immediately over a strong alternative reward, money, may have the most relevance for understanding variability in impulsive decision-making related to HPF, and associations with obesity-related outcomes. Our findings are consistent with results from cross-commodity studies with drugs of abuse, in which individuals with a substance use disorder were more likely to choose their preferred drug immediately, compared with money later, a pattern that was associated with substance use and related problems (Moody et al., 2017; Pericot-Valverde et al., 2020). Our findings also revealed that, for the most part, single commodity discounting tasks had less utility in predicting the obesity-related outcomes and had poorer fit to the data than the cross-commodity conditions. The pattern of findings is also consistent with the results of one prior cross-commodity study with alcohol that found greater predictive utility for alcohol use and problems with a cross-commodity task (Moody et al., 2017). Finally, the findings indicated that the small magnitude conditions were overall more strongly associated with the outcomes of interest compared with the large magnitude conditions. The large magnitude conditions with food may have had more limited ecological validity and therefore less predictive utility for the obesity-related outcomes. In summary, considering that single commodity discounting tasks with money or food have been inconsistently associated with obesity-related outcomes in the literature (Barlow et al., 2016; Tang et al., 2019), researchers may consider using a small magnitude, cross-commodity task comparing HPF and money when examining obesity-related outcomes.

Another finding of interest was that individuals with excess HPF intake, higher HPF craving, and higher BMIs tended to choose HPF when available immediately (when money was the delayed reward); however, they were not more willing to wait for HFP when available at a delay. Thus, their preferences for HPF were primarily expressed in the absence of a time barrier. Overall, the general assumption in the discounting literature has been that individuals with obesity and related risk factors (excess HPF intake and HPF craving) have a general impulsive decision-making style in which they are unable to wait for a reward. Overall, the effects did suggest that individuals with excess HPF intake, higher craving, and elevated BMIs may have a general tendency toward impulsive decision making that may be exacerbated in an obesogenic environment that provides wide, immediate access to HPF (Swinburn et al., 2011).

The study has several limitations. First, the study was cross-sectional and thus causality cannot be inferred from the findings. In addition, the delay discounting task used hypothetical reward for money and food. Although it is possible that hypothetical reward may not elucidate the same response patterns as real reward, prior work has demonstrated that in discounting tasks responding to hypothetical monetary reward closely aligns with responding for real monetary reward (Matusiewicz et al., 2013) and real food reward (Robertson & Rasmussen, 2018). In addition, the study used self-reported height and weight to calculate BMI, which may be vulnerable to reporting biases (Rowland, 1990). Self-reported height/weight has been found to be particularly problematic when researchers categorize weight status from BMI, as it may result in weight class misclassification (Keith et al., 2011; Preston et al., 2015). Thus, we used BMI as a continuous variable in analyses. Regarding sample characteristics, the sample was mostly white (>70%) and had some college education. Thus, it is unclear how the findings from the study may generalize to individuals from racial or ethnic minority groups, as well as those with less education. Also, there may be some overlap between discounting of HPF and behavioral demand for HPF, which could not be elucidated from our study, as behavioral demand for HPF was not measured. Future research should investigate the degree to which the two constructs may overlap and/or work together to influence discounting of HPF. Additionally, some conditions produced low indifference points even at short delays, which may have resulted in a restriction of the range of effects we were able to detect in analyses. Finally, the current study selected a standard conversion value for food and money ($2.50 = one serving of food); however, the conversion value may subjectively differ across individuals. Future work should further examine whether there may be variability in the subjective value of the commodities across individuals.

Conclusions

Findings from a general population sample indicate that choice impulsivity may be specifically related to foods that are highly rewarding to consume, as opposed to food more generally. In addition, findings highlighted the utility of using cross-commodity discounting conditions for examining obesity-related outcomes. Notably, results suggest that individuals with excess HPF intake, higher HPF craving, and higher BMIs may exhibit a general tendency toward impulsive decision making that may be exacerbated in an obesogenic environment replete with HPF. Obesity prevention efforts may consider targeting HPF availability at the environment level, to decrease convenience in accessing HPF in the food environment.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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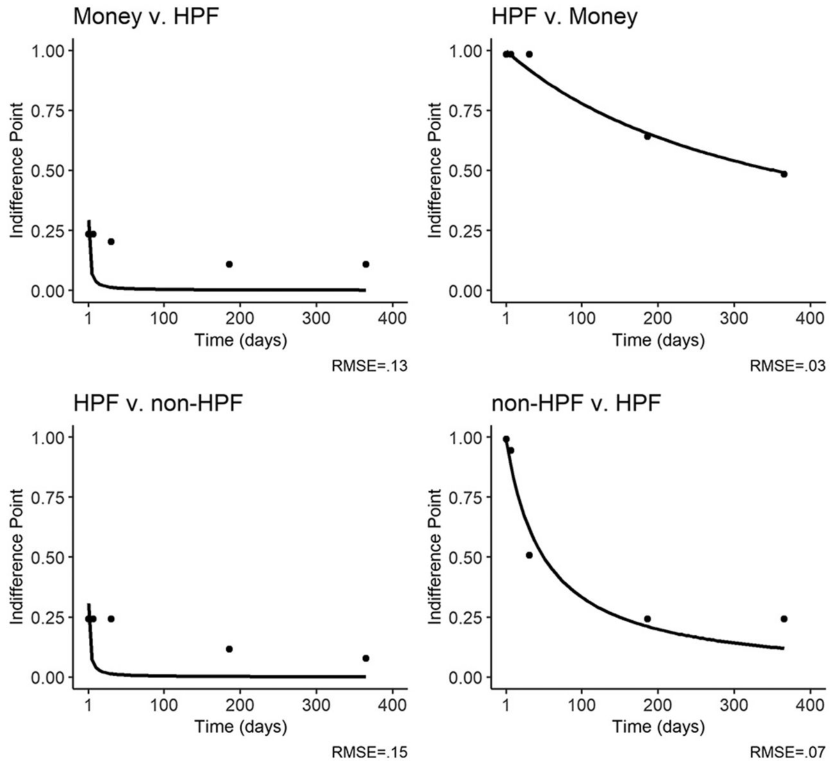

Figure 1. The Median Indifference Point as a Function of Delay in Days for Cross-Commodity Conditions

Note. HPF = hyper-palatable food; non-HPF = non–hyper-palatable food; RMSE = root mean squared error. The fit displayed corresponds to summarized data. Median indifference points calculated as per Mazur’s (1987) hyperbolic model.

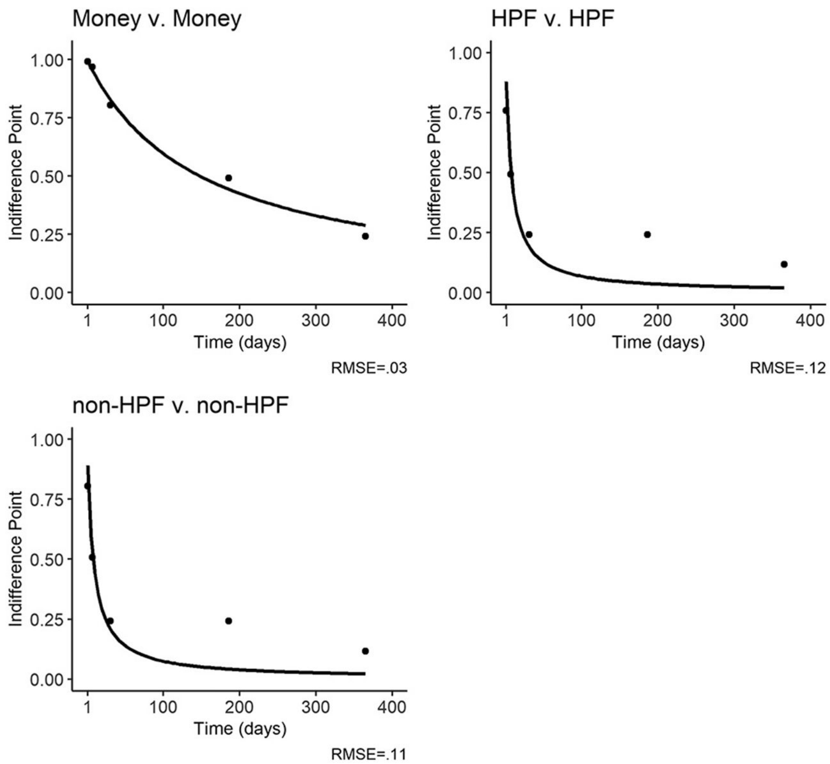

Figure 2. The Median Indifference Point as a Function of Delay in Days for Single-Commodity Conditions

Note. HPF = hyper-palatable food; non-HPF = non-hyper-palatable food; RMSE = root mean squared error. The fit displayed corresponds to summarized data. Median indifference points calculated as per Mazur’s (1987) hyperbolic model.

Table 1

Single and Cross-Commodity Conditions Used in Delay Discounting Task

Condition type	Condition	Magnitude of Delayed Commodity[a]
Single commodity	Money vs. money	$10
	Money vs. money	$100
	HPF vs. HPF	4 servings
	HPF vs. HPF	40 servings
	Non-HPF vs. non-HPF	4 servings
	Non-HPF vs. non-HPF	40 servings
Cross commodity	HPF vs. non-HPF	4 servings
	HPF vs. non-HPF	40 servings
	Non-HPF vs. HPF	4 servings
	Non-HPF vs. HPF	40 servings
	Money vs. HPF	4 servings
	Money vs. HPF	40 servings
	HPF vs. money	$10
	HPF vs. money	$100
	Money vs. non-HPF	4 servings
	Money vs. non-HPF	40 servings
	Non-HPF vs. money	$10
	Non-HPF vs. money	$100

Note. HPF = hyper-palatable food; non-HPF = non–hyper-palatable food. Immediately available commodity listed first, followed by delayed larger commodity for each condition.

[a]Exchange rate was set at $2.50 = one serving of food.

Table 2

Participant Characteristics (N = 284)

Variable	*M* (*SD*) or *N* (%)
Age	38.20 (10.96)
Gender	
Female	165 (57.5%)
Male	118 (42%)
Transgender	1 (.5%)
Race	
White/Caucasian	208 (73%)
Black/African American	22 (8%)
Asian/Pacific Islander	26 (9%)
Native-American/American Indian	3 (1%)
More than one race, non-Hispanic/Latino	6 (2%)
Other	19 (7%)
Ethnicity	
Hispanic/Latino (with any other race)	19 (7%)
Education	
<High-school GED	1 (.5%)
High-school GED or equivalent	30 (10.5%)
Some college, no degree	58 (20%)
Postsecondary degree	123 (43%)
Graduate/Professional degree	42 (15%)
Not reported	30 (11%)
Income	
<20k	28 (10%)
20k–49,999	79 (27%)
50k–99,999	107 (38%)
100k+	44 (16%)
Not reported	26 (9%)
Employment	
Full/Part time	208 (73%)
Unemployed/Disabled	47 (17%)
Not reported	29 (10%)

Note. GED = general education development certification.

Table 3

Logistic Regression Models With Small Magnitude Discounting Conditions and Excess HPF Intake (N = 279)

Model no.	Condition	*OR*	*SE*	*p* value	CI	AIC
Model 1	HPF vs. money	1.11	0.04	.008	1.03, 1.20	365.26
Model 2	HPF vs. non-HPF	1.09	0.04	.051	1.02, 1.17	366.44
Model 3	HPF vs. HPF	0.99	0.04	.798	0.92, 1.07	372.44
Model 4	Money vs. HPF	0.99	0.03	.727	0.92, 1.06	372.39
Model 5	Non-HPF vs. HPF	0.97	0.03	.786	0.91, 1.03	371.24
Model 6	Money vs. money	1.02	0.04	.598	0.94, 1.11	372.23
Model 7	Non-HPF vs. non-HPF	0.99	0.03	.844	0.93, 1.06	372.47

Note. *OR* = odds ratio; *SE* = standard error; AIC = Akaike information criteria; CI = 95% confidence interval; ln(*k*) = log transformed *k* value; HPF = hyper-palatable food; non-HPF = non–hyper-palatable food; no. = number. *p* values were adjusted using the Hochberg method.

Table 4

Linear Regression Models With Discounting Conditions and Hyper-Palatable Food Craving (N = 281)

Model no.	Condition	*B*	*SE*	*p* Value	R^2	CI	AIC
Model 1	HPF vs. money	0.050	0.010	.003	0.08	0.030, 0.070	−236.65
	Hunger	0.003	0.001	.013	—	0.001, 0.006	—
Model 2	HPF vs. non-HPF	−0.010	0.010	.796	0.02	−0.020, 0.020	−219.19
	Hunger	0.004	0.001	.003	—	0.001, 0.006	—
Model 3	HPF vs. HPF	−0.010	0.010	.798	0.02	−0.030, 0.020	−219.20
	Hunger	0.004	0.001	.003	—	0.001, 0.006	—
Model 4	Money vs. HPF	−0.020	0.010	.150	0.04	−0.040, 0.000	−223.01
	Hunger	0.003	0.001	.009	—	0.001, 0.006	—
Model 5	Non-HPF vs. HPF	−0.010	0.010	.796	0.02	−0.020, 0.020	−219.19
	Hunger	0.004	0.001	.004	—	0.001, 0.006	—
Model 6	Money vs. Money	0.040	0.010	.006	0.06	0.020, 0.070	−228.69
	Hunger	0.004	0.001	.003	—	0.001, 0.006	—
Model 7	Non-HPF vs. non-HPF	0.010	0.010	.844	0.03	−0.010, 0.030	−219.91
	Hunger	0.004	0.001	.002	—	0.001, 0.006	—

Note. *B* = β value for unstandardized estimates; *SE* = standard error; AIC = Akaike information criteria; CI = 95% confidence interval; FCI = Food Craving Inventory total score; ln(*k*) = log transformed *k* value; HPF = hyper-palatable food; non-HPF = non-hyper-palatable food; no. = number. Regression models controlled for current hunger rating. *p* values were adjusted using the Hochberg method.

Table 5

Linear Regression With Small Magnitude Discounting Conditions and Body Mass Index (N = 283)

Model no.	Condition	*B*	*SE*	*p* value	R^2	CI	AIC
Model 1	HPF vs. money	0.360	0.120	.004	0.03	0.130, 0.590	1,015.56
	Hunger	0.012	0.012	.319	—	−0.012, 0.035	—
Model 2	HPF vs. non-HPF	0.060	0.100	.796	0.01	−0.140, 0.260	1,060.57
	Hunger	0.016	0.012	.186	—	-0.008, 0.040	—
Model 3	HPF vs. HPF	−0.040	0.120	.798	0.01	−0.280, 0.200	1,060.78
	Hunger	0.017	0.012	.162	—	−0.007, 0.041	—
Model 4	Money vs. HPF	−0.040	0.110	.727	0.01	−0.250, 0.170	1,060.76
	Hunger	0.016	0.012	.190	—	−0.008, 0.040	—
Model 5	Non-HPF vs. HPF	−0.070	0.100	.796	0.01	−0.260, 0.120	1,060.42
	Hunger	0.015	0.012	.208	—	−0.009, 0.039	—
Model 6	Money vs. money	0.240	0.130	.136	0.01	−0.020, 0.500	1,057.54
	Hunger	0.016	0.012	.172	—	−0.007, 0.040	—
Model 7	Non-HPF vs. non-HPF	0.050	0.110	.844	0.01	−0.160, 0.260	1,060.65
	Hunger	0.017	0.012	.153	—	−0.006, 0.041	—

Note. *B* = β value for unstandardized estimates; *SE* = standard error; AIC = Akaike information criteria; CI = 95% confidence interval; FCI = food craving inventory total score; ln(*k*) = log transformed *k* value; HPF = hyper-palatable food; non-HPF = non–hyper-palatable food. Regression models controlled for current hunger rating; no. = number. *p* values were adjusted using the Hochberg method.