A computational model of food choice: Utility optimization through external cuing and heuristic search

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Abstract

The field of economics tends to view decision-making through a lens of assumed rationality and utility maximization. Unfortunately, choices in reality tend to be more complicated than perfect conscious value assignment. One such type of decision-making is food choice, which incorporates not only many inherent values (health, taste, price, energy), but also exists in a world of many external influences (marketing, social pressure). The details of the space in which choices are made can be highly influential, disrupting the typical top-down attentional decision-making assumed with a *homo economicus*. This paper seeks to utilize a behavioral experiment, eye-tracking, and a novel computational model (the drift diffusion model) in an effort to explore how humans make food decisions. The drift diffusion model links the metrics, reaction time, gaze fixations, and eye movement path length and frequency to the probability of subsequently choosing each item. The model takes into account not only the intrinsic attractiveness of each item, but also the context surrounding them, creating group distributions as well as individual distributions for parameters of the decision process. This paper aims to look at various aspects of food decisions: how do personal internal states, visual salience, and external cues effect how one weights the multiple value characteristics of food.

JEL Classification Numbers: D8, D80, D87

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I. Introduction

In current economics decision-making theory, we assume rationality and fully informed agents who maximize a well-defined utility function over the items they consume. In neuroscience, this translates to a focus on high-level cognitive control and top-down attention. However, making choices in real life is almost always more complicated than conscious value assignment, because parsing out relevant information is often costly in time and energy, and we encounter secondary factors such as visual cues, often overlooked in many experimental designs, that trigger the use of heuristics: mental shortcuts that ease the cognitive load of making a decision, often resulting in a satisfactory but perhaps not optimal decision. In certain real-life situations, subtle targeting of low-level salience, the state or quality by which an item stands out relative to its environment and thereby draws attention – such as ease of availability, larger font, and brighter luminance – may be even more effective in influencing choices than overtly targeting goal-direction. Furthermore, when faced with decisions that require the assessment of conflicting goals or attributes, bringing ones attention to one or the other may have large effects in how those attributes are weighted, despite natural preferences. This paper explores fixed effects regression models and drift diffusion models of decision-making that incorporate the inherent values of visual salience, external priming cues, and individual internal states.

A particularly complex facet of decision-making, self-control has immense potential to be influenced by salience properties of visual display. Self-control in food choices is of particular interest, because it sometimes asks us to pursue a long-term goal, like health, by rejecting immediate pleasures, like a sugar high, that conflict with that goal. We make food choices in several different circumstances: in different environments, under different pressures – be that time pressure or social pressures, and with different goals in mind. This project shows that, in certain situations, manipulating visual features would be an effective way to encourage the making of healthier dietary choices than explicitly directing focus to health benefits. The project uses data from eye tracking and choice behavior involving food items and non-food items to build regression models and a computational drift diffusion model (DDM) that predicts how visual features and health attributes of an item combine to capture attention and drive food choices.

II. Literature Review

There are currently many public health efforts to modify the environment in which food choices are made. One strategy has been to shield consumers from the low-cost, unhealthy foods through proposals to restrict the sale of fats and sweets, cap the marketing of soft drinks, or impose taxes to discourage snack consumption. The opposite side of the coin is to improve access to healthier options, including vegetables and fruit. Currently, fresh vegetables and fruit are not only more expensive on a per calorie basis than are fats and sweets, but also less likely to be available in low-income neighborhoods. The below graph, Figure 1, shows a clear conflict in value maximization when making decisions among food choices. Among the efforts to redress such disparities are the USDA fruit and vegetable pilot program for schools and the USDA Senior Farmers' Market program, both of which aim to provide a variety of fresh fruits and vegetables to limited-resource groups (Drewnoski & Darmon, 2005).

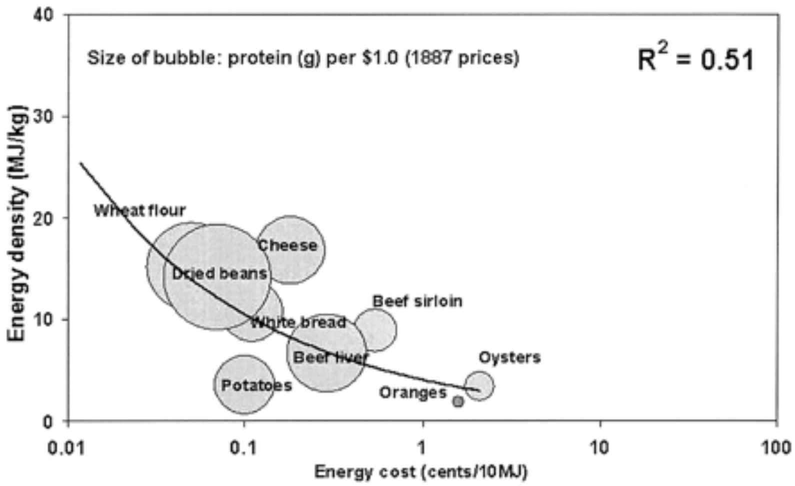


Figure 1: Graph of cost versus energy density of certain foods. Bubble size represents protein density. (Drewnoski & Darmon, 2005)

Another complication of this particular decision-making process is that assessing the nutritional value of food choices, in some respects, is less an experience attribute than a credence attribute where the consumer has difficulty assessing quality even after consumption. Consumers are unable to accurately link a particular food item with an incidence of illness or poor health, especially long-term effects from vitamin deficiencies or overconsumption of sugars. Economic models that rely on quality assessment of choices are insufficient when discussing credence goods, because the information is so imperfect that markets do not function well (Caswell & Mojduszka, 2014). Thus, the most important step in this process is quality signaling done by the market – the government must play a role in making feasible for consumers to assess the nutrition of choices via labeling, an external cue of healthfulness.

In a paper by Baranowski et al., behavioral and social science theories attempting to understand these eating behaviors are laid out (2012). Many steps of an eating action are described, starting from a simple yes or no to a final question of how long to eat. Each step can be mediated by environmental, psychosocial, behavioral, and biological variables, and thus is a potential point for influencing eating choices. Real-world food choices involve an overwhelming amount of information to process. In cases where gathering information is costly in time and energy, heuristics are employed.

In the real world, latent cues are far from irrelevant, but the majority of decision-making research is done in simplistic laboratory set-ups that ignore such details. When making complicated subjective judgments that involve uncertainty, it is necessary to adopt shortcuts, decision heuristics. Subconsciously taking into account certain perceptual aspects of stimuli is one such heuristic that sometimes are overlooked in experimental paradigms. In certain situations, varying visual salience of certain display aspects can heavily influence the valuation of options. For example, in Weber and Kirsner (1997), subjects showed a relative preference for a riskier gamble, when the highest rather than the lowest outcome of the lottery was visually emphasized, supporting the claim that unequal perceptual saliences of different outcomes can drive the calculation of choice utility.

Regrettably, more than one-third of the adults in the United States are obese, and obesity-related conditions including heart disease, stroke, type 2 diabetes, and certain cancers are some of the leading causes of preventable death. It is clear that public policy needs to find more efficient strategies to reach the entire population. It would seem as though directing attention to the health aspects of food is the most obvious signal to induce making better dietary choices, and, in some cases, overt health cues can indeed be effective. This notion is supported by a study by Hare et al. (2011), in which non-dieting human subjects performed food choice tasks in three blocks – cued to think about (1) healthfulness and (2) tastiness of foods, and (3) an un-cued decision block. Exogenous cues that directed attention to the healthfulness of food improved dietary choices. Healthfulness of food also led to higher signals in the ventral medial prefrontal cortex, (considered a value center of the brain as well as emotion-regulating) modulated by the dorsal lateral pre-frontal cortex (implicated in executive functions including cognitive flexibility and planning – decision making) when in the presence of health cues. The key finding here is that voluntary self-control can be triggered by external cues – a point we look into further with our experiment.

It is clear that future studies are needed to characterize the specific contributions of external cues and triggers to think about health or taste to the mechanisms of self-control during health-related decisions (Jasinska et al., 2011). Priming is defined as "a unconscious form of memory that involves a change in a person's ability to identify, produce, or classify an item as a result of a previous encounter with that item or related item" (Schacter et al., 2004). This is of interest to those who study decision-making, because it has the potential to influence value assignment and subsequent choices.

However, there is evidence that obvious signaling towards the importance of healthfulness many times has no effect or may even cause the exact opposite of the desired effect. One such situation that differs in real-life than an experimental setting is that typically we have more than a few seconds to make a choice. We mull over choices at the grocery store, we take time to consider all the options on a menu. Even when we create a grocery list in advance, we are prone to being influenced by visual cues: temptation to buy unhealthy snacks, choosing the brightest most centrally located option. There exists an "application effect" found by Armel et al. (2008), in which the longer someone has to look at options, the more likely they will pick an appetitive option over an aversive option, confirming the obvious: if someone weights tastiness more than healthiness, tasty foods will become more tempting as time passes in the decision process, drowning out any potential positive health cue effects.

It seems as though increasing visual and physical salience takes advantage of the human use of heuristics, mental shortcuts when making decisions when gaining more information is costly. This behavior is a departure from the classic *homo economicus* that is fully informed. It is clear that as time goes on, more nutritional information inundates our experiences. A research paper published by the Economic Research Service of the US Department of Agriculture showed that Americans may be making decisions on this increased nutrition information (as well as lower medical costs overall), but there is a general offsetting of cumulative health effect on their total diets with increased calories and added fats and oils (Blaylock et al., 1999). It seems that the forces of rising incomes, time constraints, and moderate food prices are outweighing nutritional and health information. From this study, it is clear that there exist many factors outside the consumer's control that influence food consumption behavior.

Further support for a latent cue to influence dietary choices is the case of required calorie counts on menus in New York City's restaurant and coffee chains. A law passed in July of 2008 aimed to inform patrons and aid them in making healthier choices, actually had little influence on consumer behavior ("New York's calorie counting", 2011). A broad analysis in 2011 was run comparing surveys one year before and nine months after the calorie count posting. It looked at all fast-food chains in New York City and collected receipts from approximately 15,000 consumers. Average calories bought showed no change, and only one in seven people said they had actually utilized the information. Those who did take into account the calorie count only purchased on average 96 fewer calories per order than others. Importantly, the three chains (McDonald's, Au Bon Pain, KFC) that did show significant drops in calories per customer were those that actively improved their low-calorie options. This analysis highlights how integral the restaurants' tactics are on affecting consumer choices – much more influential than just adding calorie labels. Food-related choices are highly complex and cannot always be changed simply by the disclosure of more nutritional information.

One sort of salience manipulation is simply altering accessibility of certain items. For example, reorganizing the presentation of food can be quite successful, for children especially; their decisions are more easily persuaded, allowing for salience to be a bigger factor when making choices. One such application is making the healthier food more easily accessible in a school cafeteria (Thaler & Sunstein, 2009). By moving around what items were at eye-level and moving more indulgent foods such as dessert to a separate line, increased or decreased consumption of many food items by as much as 25%. Could we translate this to the checkout line effect? Food items placed in checkout lines are typically bought on impulse, and currently candy monopolizes these shelves (Rook & Hoch, 1985). Perhaps replacing these sugary snacks with healthier food items, such as fruit or healthy protein bars, would be an effective nudge towards eating more nutritiously.

Similarly in a behavioral economics experiment, it was shown that a higher rated sandwich was only clearly preferred over a moderately rated sandwich, if the schedules of the two options (the work they'd have to put in to obtain said food item in terms of minutes they had to walk) were equal (Lappalainen & Epstein, 1990). As it became more difficult to obtain a higher rated sandwich, people were more likely to just opt for the moderately rated sandwich. Subjective taste liking is confounded by schedule constraints in food choice determination.

Another situation in which adults could be influenced through a low-level manipulation, is when we have to make quick choices, such as hastily choosing a snack out of a vending machine when you're hungry, especially when choices being considered are similar in appeal to the chooser. A manipulation, as simple as making healthy items more brightly lit, could be effective. Milosavljevic et al. studied plain luminance salience's effect on snack choices (2012). The study found that when the subject's preferences were similar between the choices, the brightened item was chosen significantly more than the non-brightened choice was. Salience can have a significant influence on choice when exposure to choices is shorter.

Another type of simple visual manipulation that could affect choice is location of item placement, as illustrated by several studies. Based on eye-tracking studies, when presented an array of options, consumers tend to give more visual attention to and more often choose the centrally located option (Atalay et al., 2012). The middle option on the supermarket shelf was preferred 71% of the time. This can be easily implemented to draw visual attention to healthier options in a menu of a fast food restaurant, rows of chips in a vending machine, or a selection of cereals on a grocery store shelf[1].

Features in which salience manipulation could be easily implemented are marketing and packaging/labeling of food products. One way in which salience comes into play in everyday decisions is when brand is taken into account to when comparing items, like when shopping for

[1] The clear economic value of optimal product placement in stores, end-aisle displays and eye-level shelf

standard groceries with lots of choices. In 2008, Van der Lans studied the visual salience in the sense of brand relevance. Brands were considered more or less prominent based on in-store activity, such as shelf space and positioning, and out-of-store activity, such as package design and advertising. Van der Lans posited that almost all competition between brands is visual, and the more visually recognizable a brand is and the more differentiated it is from competing brands, the easier consumers were able to find them in a search, suggesting that their attention would be naturally directed to these brands in real-life decision, making them more likely choose them on impulse. It follows that the more exposure consumers have to healthy items outside of the store via advertising and striking brand logos as well as in-store via eye-catching packaging design and shelf positioning, the more likely they will be to choose them.

The salience of a label is clearly integral to the visual representation of choices, and the most attention-grabbing aspect of a label is the photo according to eye-tracking data (Piqueras-Fiszman et al., 2012). Following the finding by Van der Lans (2008), the way to optimize labels to maximize brand recognition is to focus on eye-catching graphics over information disclosure of the food item. These findings support the notion that more visual attention can influence valuation; drawing attention to the photo (rather than health-conscious text) on the label of healthier foods could be an effective way to subtly influence consumers to assign higher overall values to the healthy choices.

III. Experimental Design

Though current decision-making research focuses on a top-down model of value calculation, influencing dietary choices may be more effective through targeting bottom-up processes, through manipulations as simple as enhancing visual salience. However, another clearly influential manipulation is external cues to particular attributes being assessed during the decision process. The experimental design employs behavioral and eye-tracking paradigms that look to lay the groundwork for future studies and is designed to answer the basic questions: What are the features of an item, such as a food or supplement, that best capture attention and lead to subsequent choice of that item? How do visual salience and external priming for health or taste affect the decision-making process? Successful investigations of these two questions will provide proof-of-concept for our full strategy involving real-world behavioral interventions and generate testable hypotheses regarding which methods of facilitating healthy decision-making will be most successful.

The experiments use eye tracking and choice behavior involving food items and non-food items. The participants were first given an external cue, an instruction prompt. Then they shown pairs of images of these items and asked to choose one to consume. There were a total of 25 food items, and each subject was asked to choose between every possible permutation, totaling to 300 trials (see all food items in Appendix C). Participants were shown images of food items in one block and then non-food items in the subsequent block. There were 12 non-food items (see all non-food items in Appendix C). Previous studies have shown that patterns of looking during this comparison phase accurately predict their real life choices. After the behavioral task, rated each food item for its desirability, taste, and health, and each nonfood item on desirability, utility, and enjoyment gleaned from that item – measuring a personal, subjective value for that item for each subject.

Because every possible permutation was presented to the participants, not every choice was a clear-cut unhealthy vs. healthy choice (many of the items were rated as an intermediate on the scale). This is important, as the experiment actually was able to capture some of the more convoluted decision processes when the choices are not between drastically different items across: health, taste, desirability, visual salience, and brand awareness.

The study manipulated external cuing by presenting the subjects with a priming article to read. The prompts alluded to health, taste, or nothing (control). Professor Fitzsimons at the Fuqua School of Business graciously shared the health prompt with us. For the taste cue, we used a prompt that talked about the French style of eating, which emphasizes taste. For the control prompt, the instructions presented were minimal and lacked any health or taste Slant. One can find all articles in Appendix A.

The study investigated how visual features of the items (brightness, contrast, etc.) interact with value features (Do I value the item highly? Is it a relatively healthier or unhealthier item?) to influence choices. These objective visual saliences were determined by using algorithms available on the MATLAB Saliency toolbox that the Towel et al. created (2013). With this variable, we hope to derive the importance of visual salience in the decision-making process, and how it interacts with value and external cues.

The subjects were also given a decision block of non-food items. This block serves as a control and will be crucial step when moving forward into the functional magnetic resonance imaging (fMRI) stage of this multi-step project. The brain-imaging portion of the project to be done this summer will look to see if the ventral medial pre-frontal cortex (vmPFC), a well-established neural value assessment center, is implicated similarly between food and non-food items (Hare et al., 2009). It will be interesting to see if food choices utilize a more basic part of the brain: the paralimbic cortex – in particular the insula, which plays a role in a variety of highly conserved functions related to basic survival needs: taste, visceral sensation, and automatic control (homeostatic functions). This will answer the question of whether food decision-making process also relies on a different system alongside the typical vmPFC valuation system.

Though this honors thesis does not cover the brain correlates of the decision-making process, it will be relevant in the sense that it well explore the general choice between utility and hedonic (enjoyment and pleasure) experience – a sort of foil to the choice between nutrition and taste. The non-food items will include $15 gift cards to a multitude of venues, ranging from Staples to Stubhub (see all non-food items in Appendix C). Each subject then rated the gift card choices on the following scales: utility, enjoyment, and desirability. This served as a non-food multiple attribute decision-making space. Here, we aimed to see no effects of the external cues on the weighting of the value assignment characteristics, but we also used the drift diffusion model to explore the decision-making process of non-food items.

One crucial aspect of the data collection is the internal state of each subject. The metrics that effect food decisions of each subject includes the follow surveys: the Self Control Scale, the Maximization Scale, a self-created Health Consciousness Scale, and an Eating Behavior Survey that will also ask about whether the subject is dieting (see all scales in Appendix B). With these surveys, we gauge a multi-faceted look at the personal decision behaviors of each participant. We will also ask about how last night's sleep, and how restful the subject feels, as sleep may be a potential confounding factor. To control for hunger, the subjects will be asked to not eat 4+ hours before, so that they are properly motivated to choose in line with their real preferences. This will be confirmed before the behavioral task as well. This is a common and widely accepted practice in behavioral economics, psychology, and neuroscience experiments to control satiation level across subjects. Participants that were screened as having abnormal eating behaviors (anorexia, bulimia, etc.), overly exhausted, having eaten less than 4 hours ago, or nonsensically filling out the surveys were taken out of the data analysis pool.

This survey asked the participants to rate all the food items on health, taste, and desirability (How healthy is this item? How tasty is this item? How much would you like to eat this item? Scale 1, Least -7, Most). The survey also asked the participants to rate the non-food gift card choices on utility, enjoyment, and desirability. These ratings will be used to determine the variables "ΔHealth," "ΔTaste," "ΔWant," "ΔUtility," "ΔEnjoy," and "ΔWant" (rating of left item minus rating of right item) used in the Linear Probability Model and Logistic regression models to be elaborated on in the theoretical framework section. To control for pre-conceived notions of brand quality, we included in the pre-behavioral-task survey questions a general awareness of the items (Have you heard of this item? Have you eaten this item?). This generated a general sense of whether the participants have an idea of the nutrition and taste of the food choices. As for the general quality of the food items, the ranking of taste and nutrition was sufficient representation, as we will not include items of drastic quality difference.

We then used these data to build computational models: regression models supplemented by a novel computational model used more and more in neuroscience, the drift diffusion model. These various models predict how visual features, health attributes, taste attributes, etc. of an item combine to capture attention and drive choice toward the item. The drift diffusion models linked metrics such as gaze fixations, eye movement path length and frequency, and pupil diameter to the probability of subsequently choosing each item. The model took into account not only the intrinsic attractiveness of each item, but of the context surrounding it.

IV. Theoretical Framework

In economics, there exists the concept of a *homo economicus*, a human that is rational and narrowly self-interested actors who have the ability to make decisions based on their subjective goals. This concept encompasses the idea of maximizing a utility function as a consumer, which is imperfect for many reasons as seen in empirical research. In this paper, the most relevant flaws are 1) full rationality of agents, and 2) the highly variable and malleable preferences by cues such as social influences, framing, and education.

This project aims to show that when it comes to food choice, these two flaws are very much a part of the decision-making. The project runs two models: A) fixed effects LPM and Logistic regression models, and B) drift diffusion models that better illustrate the effect of all the variables on individual parameters of the decision process.

A. Fixed Effects LPM and Logistic Regression Models

The first method of modeling the food decision process is participant fixed effects regression models. The coefficients of these models explore the interaction effects of the external cue conditions (control, health, taste) on the food decision process, the effect of visual salience on the food decision process, as well as how internal states, levels of self control and health consciousness, play into the process. In all of the regressions, we held constant the difference between the choices in price and calories, to take into account maximization of economical and energy utility. The non-food trials acted as a sort of control and were regressed as well to explore the differences between how all the different aspects of the choice context effect food decisions and non-food decisions.

Food Decision Regression Models

1. $ChoiceLeft = (\beta 1\ \Delta Taste + \beta 2\ \Delta Health + \beta 3\ \Delta Want + \beta 4\ \Delta Salience) * Prime + \beta 5\ \Delta Price + \beta 6\ \Delta Calories + \varepsilon$

2. $ChoiceLeft = [(\beta 1\ \Delta Salience) * \Delta WantBins)] * Prime + \beta 2\ \Delta Price + \beta 3\ \Delta Calories + \varepsilon$

3. $RT = \beta 1\ abs\Delta Taste + \beta 2\ abs\Delta Health + \beta 3\ abs\Delta Want + \beta 4\ abs\Delta Salience + \beta 5\ abs\Delta Price + \beta 6\ abs\Delta Calories + \varepsilon$

   $RT = (\beta 1\ abs\Delta Taste + \beta 2\ abs\Delta Health + \beta 3\ abs\Delta Want + \beta 4\ abs\Delta Salience) * Prime + \beta 5\ abs\Delta Price + \beta 6\ abs\Delta Calories + \varepsilon$

4. $ChoiceLeft = (\beta 1\ \Delta Taste + \beta 2\ \Delta Health + \beta 3\ \Delta Want + \beta 4\ \Delta Salience) * SC + \beta 5\ \Delta Price + \beta 6\ \Delta Calories + \varepsilon$

   $ChoiceLeft = (\beta 1\ \Delta Taste + \beta 2\ \Delta Health + \beta 3\ \Delta Want + \beta 4\ \Delta Salience) * HC + \beta 5\ \Delta Price + \beta 6\ \Delta Calories + \varepsilon$

5. $ChoiceLeft = (\beta 1\ \Delta Health) * TimeBlock + \beta 2\ \Delta Price + \beta 3\ \Delta Calories + \varepsilon$

Non-Food Decision Regression Models

1. $ChoiceLeft = (\beta 1\ \Delta Use + \beta 2\ \Delta Want + \beta 3\ \Delta Enjoy) * Prime + \varepsilon$

2. $RT = \beta 1\ abs\Delta Use + \beta 2\ abs\Delta Want + \beta 3\ abs\Delta Enjoy + \varepsilon$

3. $ChoiceLeft = (\beta 1\ \Delta Use + \beta 2\ \Delta Want + \beta 3\ \Delta Enjoy) * SC + \varepsilon$

   $ChoiceLeft = (\beta 1\ \Delta Use + \beta 2\ \Delta Want + \beta 3\ \Delta Enjoy) * HC + \varepsilon$

The ΔHealth, ΔTaste, and ΔWant variables are determined by the difference between the participant's self-reported rating of the left choice and rating of the right choice. The ΔSalience is the normalized difference between the visual salience of the left choice's picture and the visual salience of the right choice's picture, as deemed by the system created by Towal et al. in "Simultaneous modeling of visual saliency and value computation improves predictions of economic choice" (2013). Towal et al. creates a saliency map for display images using EyeQuant Attention Analytics software, which includes standard channels such as color, intensity, and orientation, as well as shapes.

In the first block of regression models run on food decisions, the analyses' dependent variables are ChoiceLeft (participant chose the left item=1, participant chose the right item=0) or RT (response time in seconds). Response time is an important component of the decision process, as it is a proxy for the difficulty of a decision. The deliberation process aspects that RT explores are reflected also in drift diffusion modeling explored further in the following section. First, the regression models compare the variables on the three conditions' interaction terms with the weighting of taste/health/want rankings will elucidate whether external cuing can have a significant effect on how we make food decisions. In other words, how we weigh different characteristics of the choices and how long we take to make these decisions.

The effect of visual salience is determined on decisions where the ΔWant is big and small, aiming to answer the question of whether visual salience plays a bigger role when the items are similar in inherent desirability. The fixed effects model accounts for the internal states of the participant, which is also measured by the surveys. Also, we will regress the models with interactions between the internal state bins: self-control and health consciousness split at the median into low- and high- bins. We also look at whether or not the effect of the health external cue diminishes over time. These time effects will be explored by looking at interaction terms of ΔHealth and 3 time block bins.

In the second block of regression models, we look at the non-food decisions. The non-food equivalent characteristics that were used as metrics in the food decisions are: ΔUse, ΔWant, and ΔEnjoy. These seek to measure the utility, enjoyment, and desirability of the choices. We regress the weights of these characteristics as they interact with the external cue conditions as well as the internal states.

This regression modeling is in part based on the analysis done on the behavioral results of (Hare et al., 2011). When looking at their interaction term betas, the taste rating beta is strongest, but there is a significantly higher additive effect of health rating in the health block, and a decrease of the taste rating effect in health blocks. We hope to see similar results in our results.

B. Drift Diffusion Model

The model we ran in parallel with the simple regression model is a drift diffusion model (DDM). Also known as the Random walk model, posits that the subject is accumulating evidence for one or other of the alternatives, and integrating that evidence until a decision threshold is reached. The DDM has been shown to describe accuracy and reaction time in human behavior (Krajbich & Rangel, 2011; Vandekerckhove & Tuerlinck, 2008). For example, Shimojo et al. (2003), showed that visual attention reflects preference in face attractiveness (Shimojo et al., 2003). When subjects considered face pairs, the gaze was first distributed evenly, but eventually drifted more to the face subsequently chosen as more attractive.

This model utilizes reaction times and choice to run simulations and generate decision process parameters. It is given more fidelity by incorporating eye-tracking data as a proxy for attention to make the model fit better. The parameters are 1) drift rate (v), the rate at which the decision is reached during evidence accumulation, 2) threshold (a) spacing, the distance of the threshold from the baseline, and 3) bias (z) in the starting point, where the baseline starts, which is not necessarily at the midline between thresholds. A longer reaction time also suggests a more difficult decision. Drift rate can be assumed at a constant rate in the basic drift diffusion model, but using eye tracking is a more accurate proxy for drift rate.

A subject starts at time = 0 on the left at some starting point, which can be closer to the top or the bottom due to a bias (z). Then as the subject accumulates information about the two choices, he begins to drift towards the upper response boundary or lower response boundary which is half the threshold value (a) away from the unbiased starting point. When one of these boundaries, or information accumulation thresholds, is reached, the choice is made. The speed with which the decision is made is represented by drift rate (v), calculated as a probability of moving a step towards the upper response boundary with each given second. Figure 2 shows the visual of the drift diffusion process and the various parameters.

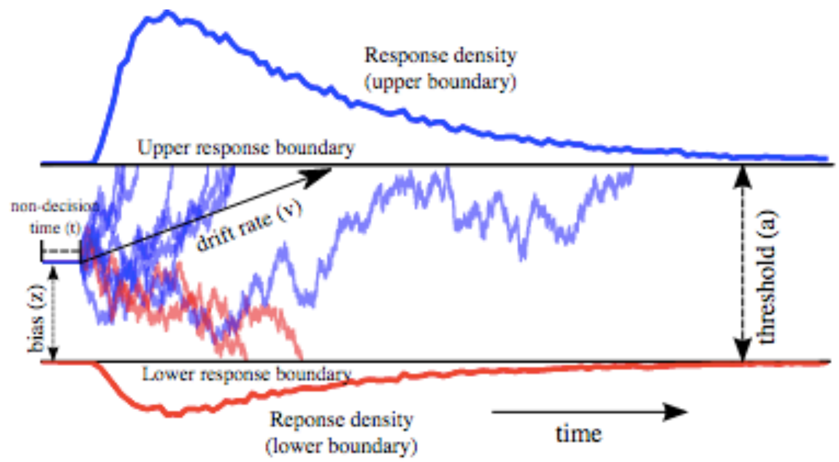


Figure 2: Representation of the drift diffusion model (Wieki et al., 2013).

The proposed theoretical framework for this paper emulates that of Towal et al.'s, in which it was made obvious that the most likely explanation of this type of multi-faceted choice is a combination of both lower-level salience and explicit value assessment manipulated by external cues. Towal et al. (2013), conducted a study using psychophysical data from a 4-item choice task, in which subjects had to pick a food item from a 2X2 display via eye movements. They tested four models where the DDM process, based on eye fixation patterns, was driven by (*i*) saliency or (*ii*) value alone or (*iii*) an additive or (*iv*) a multiplicative combination of both. The study found that models including both saliency and value weighted in a one-third to two-thirds ratio (saliency-to-value) significantly outperformed the other models. This suggests that "visual saliency has a smaller, but significant, influence than value and that saliency affects choices indirectly through perceptual decisions that modulate economic decisions" (Towal et al., 2013). We hope to show that the value variable can be manipulated by external cues like the aforementioned paper by Hare et al. (2011).

This is in line with the public policy push to strengthen and improve nutrition education as well as accessibility in schools and work sites (Story et al., 2008). An increase in classroom healthy food choice education and work site health-promotion programs could complement changes in an environment that also supports healthy eating through increasing the accessibility (a la Thaler and Sunstein's reorganization of a school cafeteria) and affordability of the healthy options. For example, a program that sent tailored nutrition education email messages to a work site showed small but significant decreases in dietary fat intake and increases in fruits and vegetable consumption (Block et al., 2004).

Using the Wieki et al.'s HDDM Python toolbox, we run simulations that take 14,000 samples from the data to create drift diffusion models to compare across a multitude of data subsets (2013). The DDM comparisons to explore the effects of external cues are as follows: 1) Overall across ΔWant Bins, 2) Across ΔWant Bins in the three external cue conditions, 3) For decisions where ΔHealth>3 and ΔTaste=0, 4) For decisions where ΔTaste>3 and ΔHealth=0, 5) Across ΔHealth Bins in the three external cue conditions. Then, the analyses also include the DDM comparisons that model the effects of internal states (self-control and 1) in food and non-food decisions.

V. Results

Data collection was not as extensive as hoped, thus there are potential inaccuracies in my findings due to data limitation. The data set used includes 44 subjects (15 control condition, 17 health condition, 12 taste condition). The conditions, as a reminder, are the type of external cue (prime), they were presented at the beginning of the task.

I. Fixed Effects LPM and Logistic Regression Models

A. Fixed Effects Regression Models on Choice Depending on External Cue Primes

$$ChoiceLeft = (\beta 1\ \Delta Taste + \beta 2\ \Delta Health + \beta 3\ \Delta Want + \beta 4\ \Delta Salience) * Prime + \beta 5\ \Delta Price + \Delta\beta 6\ Calories + \varepsilon$$

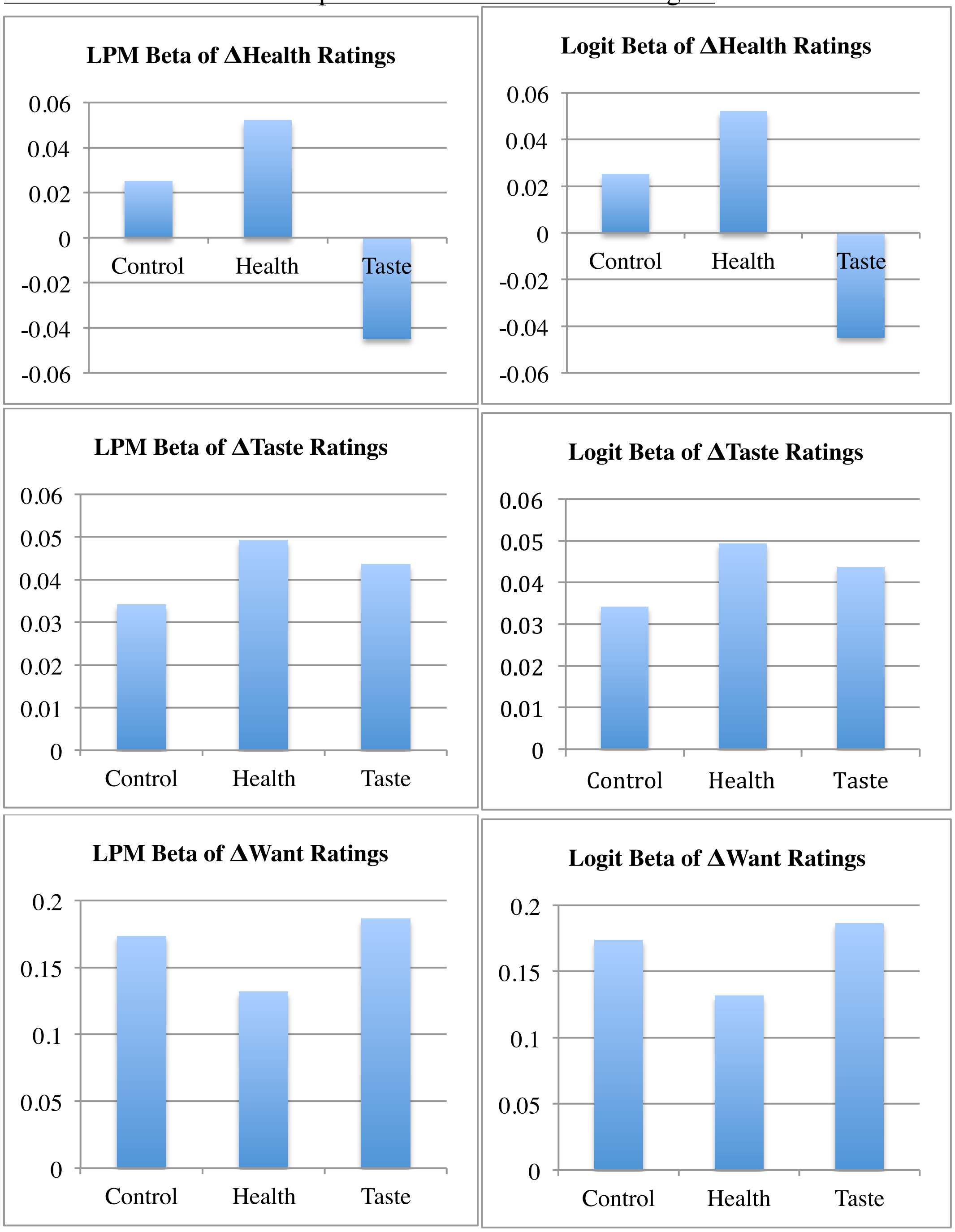
Table 1. Estimates of the Relationship Left Choice and Weighting of Characteristics (Primes)

		LPM	Logistic Model (Marginal Effects)
Control Prime	ΔHealth	-0.0022 (0.0036)	-0.0022 (0.0067)
	ΔTaste	0.0512*** (0.0047)	0.0891*** (0.0090)
	ΔWant	0.1446*** (0.0038)	0.2419*** (0.0092)
	ΔSalience	0.0115*** (0.0038)	0.1795*** (0.0068)
Health Prime	ΔHealth	0.0325*** (0.0035)	0.0561*** (0.0068)
	ΔTaste	0.0339*** (0.0053)	0.0610*** (0.0065)
	ΔWant	0.1393*** (0.0049)	0.2238*** (0.0098)
	ΔSalience	0.0007 (0.0037)	0.0010 (0.0101)
Taste Prime	ΔHealth	-0.0176*** (0.0050)	-0.0174* (0.0098)
	ΔTaste	0.0499*** (0.0069)	0.1058*** (0.0135)
	ΔWant	0.1866*** (0.0063)	0.3220*** (0.0127)
	ΔSalience	0.0087* (0.0051)	0.0047 (0.0096)
	ΔPrice	-0.0263*** (-0.0263)	-0.0047*** (0.0074)
	ΔCalories	-0.0004*** (0.0000)	-0.0007*** (0.0001)

Note: Standard errors given in parentheses
*p<0.10, **p<0.05, ***p<0.01

Table 2 below is the first of the many behavioral regression results we analyzed. These graphs show the beta weights with subject fixed effects. When they're positive, they indicate that a factor increased the likelihood of eating the food item. When they're negative, they indicate a decrease in likelihood. This same logic applies to the rest of the tables like this one follow.

Table 2. External Cue Comparisons of Characteristic Weights



Condition ΔHealth Betas are different:

X^2=71.14
P> X^2=0.0000

Condition ΔTaste Betas are different:

X^2=8.53
P> X^2=0.0000

Condition ΔWant Betas are different:

X^2=35.83
P> X^2=0.0000

The results above show the fixed effects linear probability model regression and the fixed effects logistic regression ran on the dummy variable for choosing the left item, the interaction terms between the three external cue conditions and the differences between subject's characteristic ratings of the left choice and right choice and, while holding constant the differences in price and calories. These regressions were also run with difference between rankings (subjects were also asked to order all the food items from most to least in each of the characteristics), but the results were almost identical, and thus omitted. In Table 1, one can see that in the control condition, all the variables are significant except for ΔHealth. In the health and taste conditions, all variables are significant except for ΔSalience. An interpretation for the logistic regression's marginal effect betas (these coefficients are the most easily interpreted) is as follows: in the control condition, ΔHealth has a negligible effect. However when holding everything else constant and ΔTaste increases by 1, ΔWant increases by, or ΔSalience increases by 1, there is an 8.91%, 24.19% and 17.95% higher chance respectively of choosing the left item. The same logic follows for the rest of the external cue conditions and respective coefficients.

The clearest finding is that ΔHealth is significantly more heavily weighed in the health external cue condition than in the control condition. The ΔHealth weight is actually negative in the taste external cue condition, implying that when externally prompted to think about taste, the health aspect of the choice may actually have a negative effect. Another interesting finding is that ΔWant is more important in the control condition and taste condition than in the health condition, reflecting an effort to choose the healthier options rather than the inherently more desirable options when influenced to think about health. This also proves that even when holding constant economical maximization, monetarily (price) and energy-wise (calories), the primes have a strong effect.

Looking at the X^2 values, one can see that the ΔHealth, ΔTaste, and ΔWant betas are significantly different across the conditions, implying that the external cues have significant effects on the decision process. All of differences in betas seem to indicate that when externally cued towards health, the decision-making process more heavily weights health and less about taste, steering the decision away from the unhealthier items that may be instinctively wanted. Similarly, when cued to think about taste, the healthiness of the items is actually negatively weighted and the evaluation of taste is clearly at the forefront of the decision.

B. Fixed Effects Regression Models Exploring Salience Effects Depending on Wanting

Though the ΔSalience coefficients were insignificant in the above regression for the health prime and taste prime conditions, the regression of the interaction terms between ΔSalience and ΔWant while holding ΔHealth, ΔTaste, ΔPrice, and ΔCalories constant probes whether or not salience might be more or less important depending on the discrepancy of inherent wanting of the items. There has been research done that showed visual salience can be more important to the decision-making process when there is little discrepancy in more top-down characteristic evaluations (Milosavljevic et al., 2012).

$$ChoiceLeft = [(\beta 1\ \Delta Salience * \Delta WantBins) * Prime] + \beta 2\ \Delta Taste + \beta 3\ \Delta Health + \beta 4\ \Delta Price + \beta 5\ \Delta Calories + \varepsilon$$

Note: I ran these as three separate regressions, one for each external cue, or prime, condition. I would have liked to run it as one regression like the one written above, but due to data limitations, too much collinearity occurred when running it as such.

Table 3. Estimates of Interaction between ΔSalience's and ΔWant's Effects on Choice

		LPM	Logistic Model (Marginal Effects)
Control Prime	ΔSalience when ΔWant = 0	0.0125 (0.0086)	0.0143 (0.0114)
	ΔSalience when ΔWant = 1	-0.0063 (0.0071)	-0.0103 (0.0096)
	ΔSalience when ΔWant = 2	-0.0178* (0.0093)	-0.0266* (0.0139)
	ΔSalience when ΔWant = 3	-0.0469*** (0.0118)	-0.0878*** (0.0191)
	ΔSalience when ΔWant = 4	-0.0314* (0.0167)	-0.1251*** (0.0347)
	ΔHealth	0.0204*** (0.0046)	0.0389*** (0.0069)
	ΔTaste	0.1619*** (0.0042)	0.2454*** (0.0084)
	ΔPrice	-0.0869*** (0.0072)	-0.1321*** (0.0109)
	ΔCalories	-0.0007*** (0.0001)	-0.0009*** (0.0001)
Health Prime	ΔSalience when ΔWant = 0	-0.0015 (0.0076)	-0.0038 (0.0103)
	ΔSalience when ΔWant = 1	-0.0109 (0.0068)	-0.0184* (0.0097)
	ΔSalience when ΔWant = 2	-0.0104 (0.0088)	-0.0169 (0.0144)
	ΔSalience when ΔWant = 3	-0.0075 (0.0108)	-0.0068 (0.0200)
	ΔSalience when ΔWant = 4	0.0055 (0.0044)	0.0333 (0.0569)
	ΔHealth	0.0557*** (0.0044)	-0.0038*** (0.0070)
	ΔTaste	0.1483*** (0.0039)	0.2374*** (0.0081)
	ΔPrice	-0.0535*** (0.0069)	-0.0881*** (0.0106)

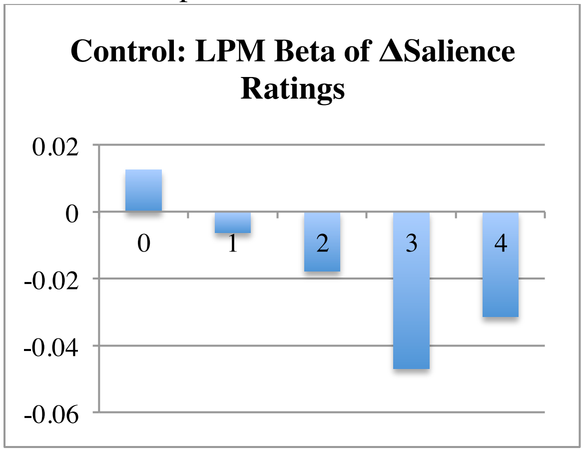
	ΔCalories	-0.0007*** (0.0001)	-0.0010*** (0.0001)
Taste Prime	ΔSalience when ΔWant = 0	-0.0090 (0.0114)	-0.0170 (0.0151)
	ΔSalience when ΔWant = 1	0.0056 (0.0091)	-0.0017 (0.0127)
	ΔSalience when ΔWant = 2	0.0243** (0.0115)	0.0229 (0.0192)
	ΔSalience when ΔWant = 3	0.0102 (0.0174)	-0.0254 (0.0352)
	ΔSalience when ΔWant = 4	-0.0407 (0.0360)	-0.1362 (0.0921)
	ΔHealth	0.0657*** (0.0067)	0.1065*** (0.0104)
	ΔTaste	0.1863*** (0.0060)	0.3009*** (0.0134)
	ΔPrice	-0.0862*** (0.0099)	-0.1338*** (0.0153)
	ΔCalories	0.0002* (0.0001)	0.0002* (0.0002)

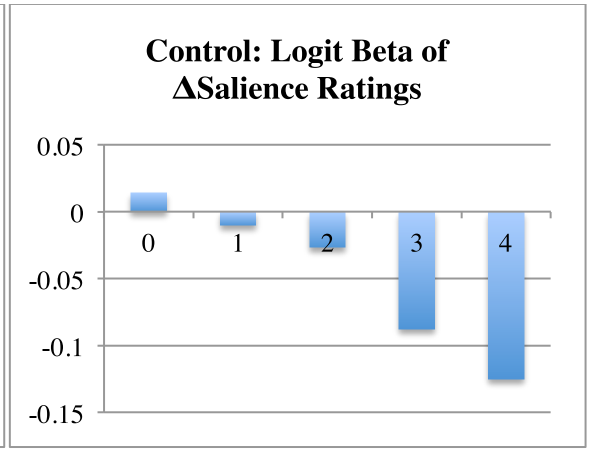
Note: Standard errors given in parentheses
*p<0.10, **p<0.05, ***p<0.01

The results did not reflect the previously discussed expectations. None of the coefficients were significant at $p<0.05$ except for when ΔWant was 2, 3 and 4, in the control condition. Significance aside, there is no clear directional pattern. In the control condition, it does seem as though the higher the ΔWant, the more negative ΔSalience's effect is, which does not make logical sense. In the health condition, it seems like ΔSalience has the highest effect when ΔWant is highest. These betas can be seen in Table 4 on the following page.

Perhaps, in these cases, the most inherently desirable items were also most visually salient, creating a confounding factor. A possible explanation of this is an unsatisfactory metric for visual salience. Due to lack of expertise, the visual salience metric may have been unable to capture key aspects such as text on the labeling. Additionally, an interesting though logical result here is that ΔCalories is less significant in the Taste condition.

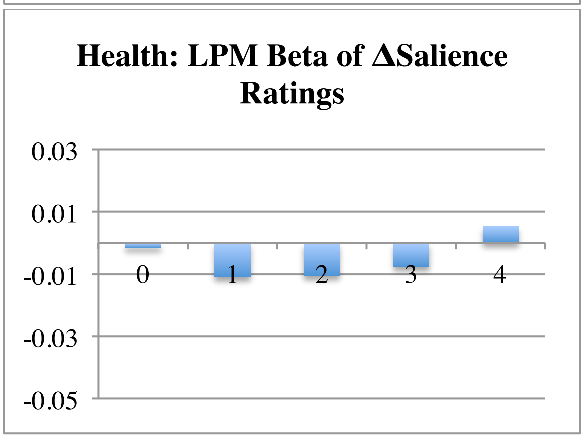
Table 4. Comparisons of ΔSalience on Choice and ΔWant Bins Across External Cues

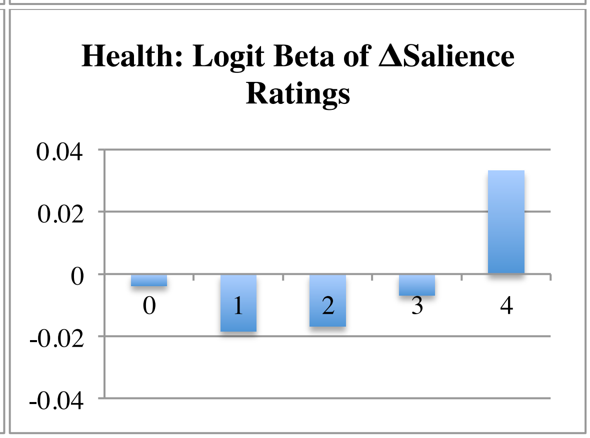




Condition ΔSalience Betas are different:

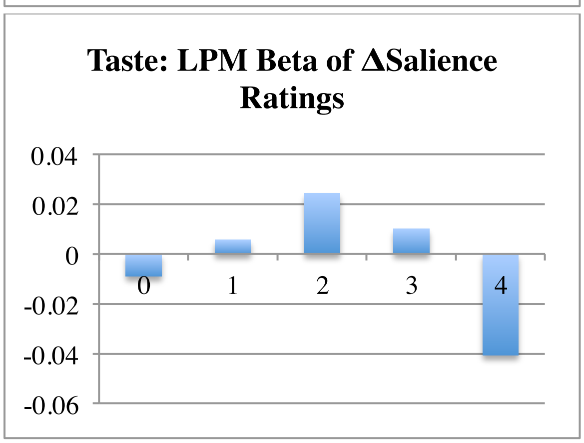
X^2=31.78
P> X^2=0.0000

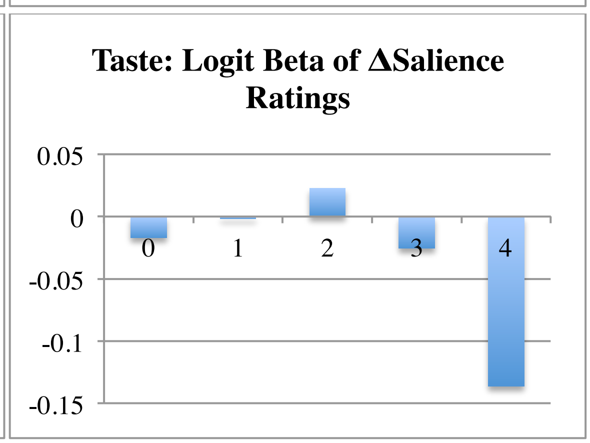




Condition ΔSalience Betas are different:

X^2=1.89
P> X^2=0.7564





Condition ΔSalience Betas are different:

X^2=51.9
P> X^2=0.2683

C. Fixed Effects Regression Models on Response Time (RT)

$$RT = \beta 1\ abs\Delta Taste + \beta 2\ abs\Delta Health + \beta 3\ abs\Delta Want + \beta 4\ abs\Delta Salience + \beta 5\ abs\Delta Price + \beta 6\ abs\Delta Calories + \varepsilon$$

Table 5. Estimates of the Relationship between RT, ΔRatings, and Primes

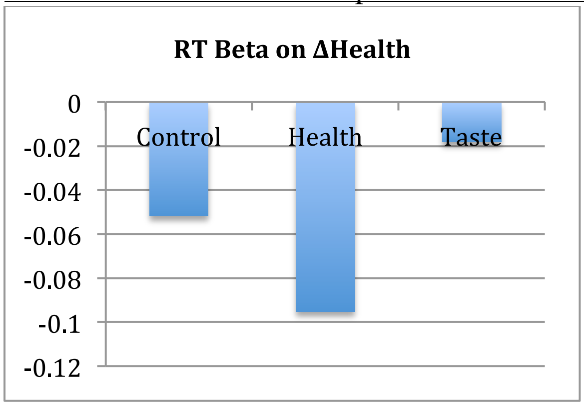
Table 6. Overall Estimates of the Relationship between RT and ΔRatings

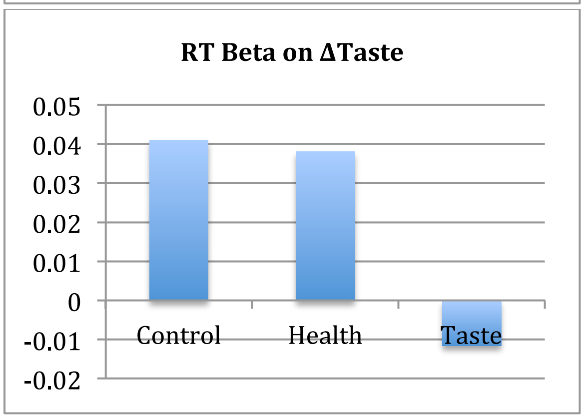
		LPM
Control Prime	absΔHealth	-0.0517*** (0.0159)
	absΔTaste	0.0410** (0.0190)
	absΔWant	-0.1465*** (0.0160)
	absΔSalience	-0.0038 (0.0203)
Health Prime	absΔHealth	-0.0953*** (0.019)
	absΔTaste	0.0381** (0.0194)
	absΔWant	-0.2339*** (0.0182)
	absΔSalience	-0.0055 (0.0234)
Taste Prime	absΔHealth	-0.0182 (0.0272)
	absΔTaste	-0.1116*** (0.043)
	absΔWant	-0.1782*** (0.0261)
	absΔSalience	0.0601** (0.0274)
	absΔPrice	0.01467 (0.0163)
	absΔCalories	-0.0001 (0.0002)

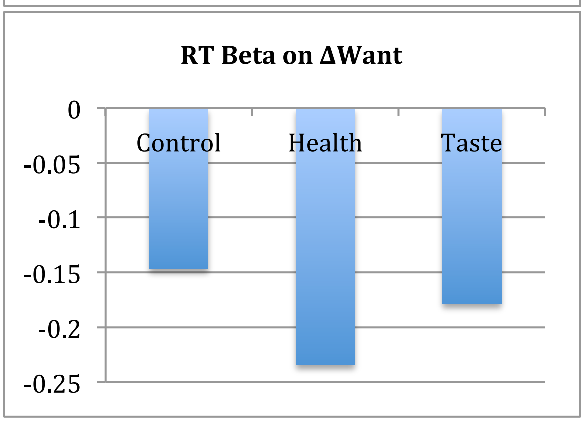
	LPM
absΔHealth	-0.0642*** (0.0108)
absΔTaste	-0.0272** (0.0123)
absΔWant	-0.1811*** (0.0109)
absΔSalience	0.0085 (0.0126)
absΔPrice	0.0128 (0.0163)
absΔCalories	-0.0001 (0.0002)

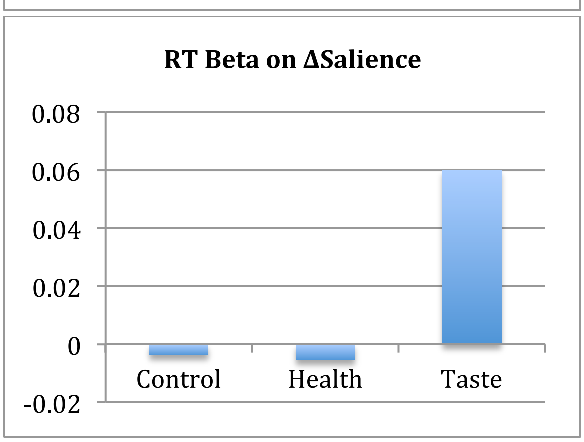
Note: Standard errors given in parentheses
*p<0.10, **p<0.05, ***p<0.01

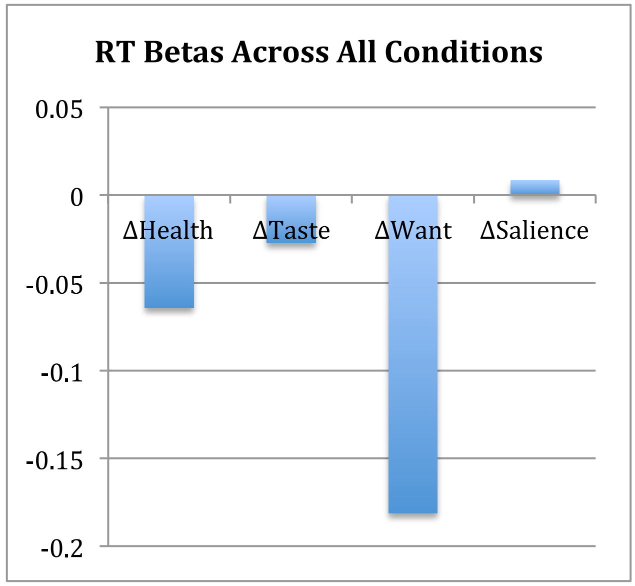
Table 7. External Cue Comparisons of Characteristic Weights on RT











Condition ΔHealth Betas are different:

F=4.09
P> X^2=0.0167

Condition ΔTaste Betas are different:

F=10.64
P> X^2=0.0000

Condition ΔWant Betas are different:

F=6.53
P> X^2=0.0015

Condition ΔSalience Betas are different:

F=2.21
P> X^2=0.1102

As one can see in Tables 6 and 7, when response time was regressed with the differences in characteristic ratings across all trials, all of the coefficients are significant except for absΔSalience. When crossed with the external cue conditions, all the coefficients are again significant except for absΔSalience across all conditions and absΔHealth in the taste prime condition. In the control condition, absΔHealth and absΔWant are significantly negatively correlated with response time, following the logic that the larger the discrepancy in the values in health and inherent desirability, the easier the choice and thus the faster the decision is made. However, absΔTaste in this control condition is positively correlated with response time, seeming to imply that as absΔTaste increases, the longer it takes the subject to make a decision, reflecting a conflict in the multiple attribute value assignment. This pattern is replicated in health prime condition, and the same logic follows. This is interesting, as it perhaps implies that the default mentality of the subjects when not prompted with any sort of external influence is a more health-centric one[2]. In the taste prime condition, absΔTaste and absΔWant are negatively correlated with RT, but absΔHealth is negligible, seemingly to imply that when cued to think about taste, the health attribute of the choice items was more often neglected.

D. FE Regression Models on Food Choices -Internal States

$$ChoiceLeft = (\beta 1 \Delta Taste + \beta 2\ \Delta Health + \beta 3\ \Delta Want + \ \beta 4\ \Delta Salience) * HC \ + \beta 5\ \Delta Price + \beta 6\ \Delta Calories + \varepsilon$$

Table 8. Estimates of Self Control Effects on Food Characteristic Weights

		LPM	**Logistic Model (Marginal Effects)**
Low Self-Control	ΔHealth	-0.0015 (0.0030)	0.0065 (0.0048)
	ΔTaste	0.0437*** (0.0038)	0.0957*** (0.0077)
	ΔWant	0.1562*** (0.0034)	0.2978*** (0.0087)
	ΔSalience	0.0058** (0.0029)	0.0070 (0.0054)
High Self-Control	ΔHealth	0.0352*** (0.0034)	0.0681*** (0.0066)
	ΔTaste	0.0435*** (0.0055)	0.0846*** (0.0102)
	ΔWant	0.1379*** (0.0046)	0.2470*** (0.0103)

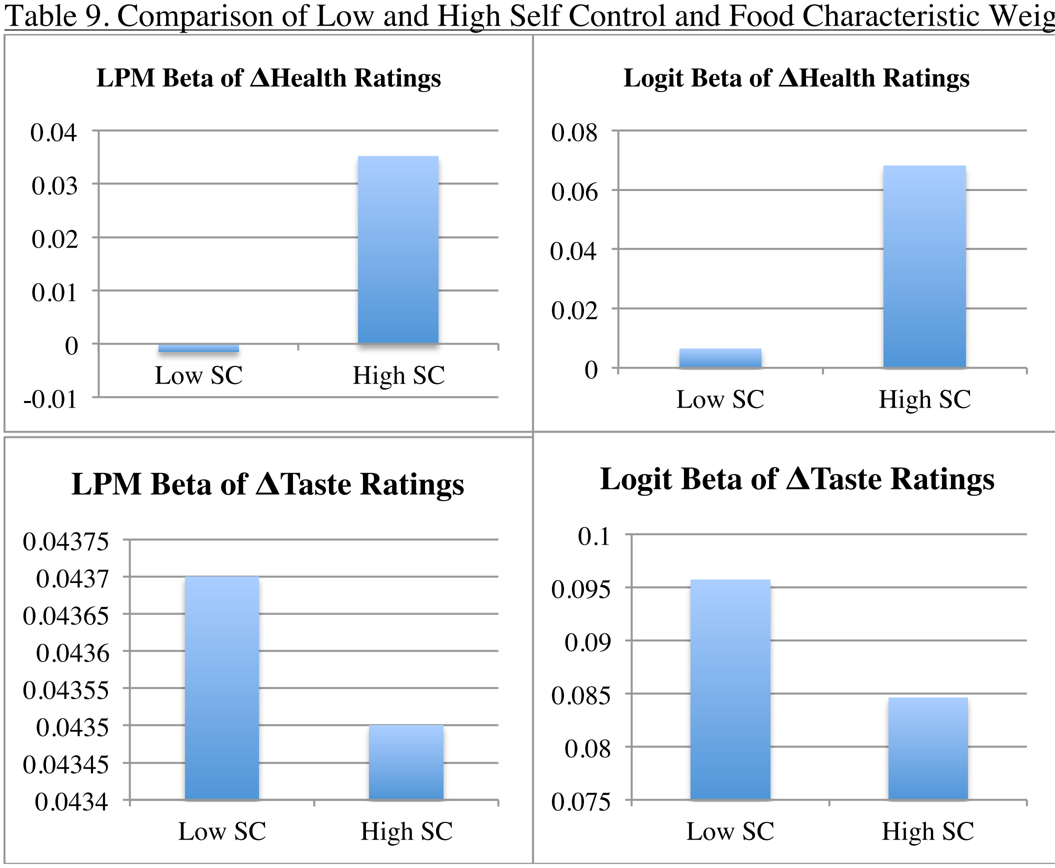
[2] This is potentially a note on the participant pool, which was mostly Duke students.

ΔSalience	0.0079** (0.0040)	0.0101 (0.0070)
ΔPrice	-0.0262*** (0.0041)	-0.0549*** (0.0076)
ΔCalories	-0.0004*** (0.0000)	-0.0007*** (0.0000)

Note: Standard errors given in parentheses
*p<0.10, **p<0.05, ***p<0.01

In Table 8, one can see that when participants are separated at the median values of self-control, a crucial internal state involved in food decision-making, there is a significant difference in the weighting of the multiple attributes of the food items. Most noticeable is the change in beta of ΔHealth: In high self-control subjects, an increase of 1 in ΔHealth at the median values results in an increase of 6.81% in the chance of choosing the left item, whereas in low self-control subjects, the effect of ΔHealth is not significantly different from 0 (X^2=55.59, P> X^2=0.0000). Also significantly different are the betas of ΔWant between the self-control groups. Low self-control subjects weighted ΔWant significantly higher than high self-control subjects. These differences are illustrated in Table 9 below.

Table 9. Comparison of Low and High Self Control and Food Characteristic Weights

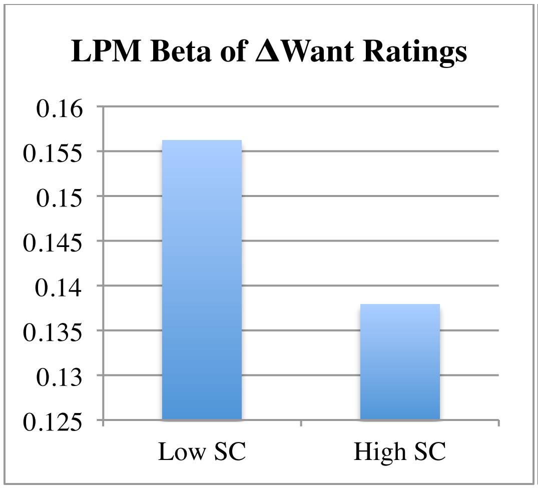


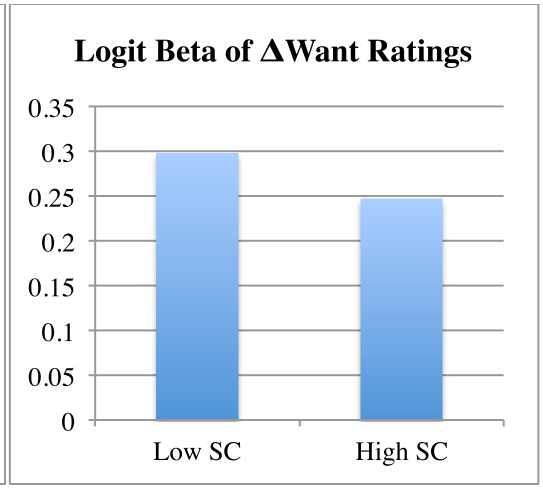
Condition ΔHealth Betas are different:

X^2=55.59
P> X^2=0.0000

Condition ΔTaste Betas are different:

X^2=0.75
P> X^2=0.3879





Condition ΔTaste Betas are different:

X^2=0.75
P> X^2=0.3879

$$ChoiceLeft = (\beta 1\ \Delta Taste + \beta 2\ \Delta Health + \beta 3\ \Delta Want + \beta 4\ \Delta Salience) * HC + \beta 5\ \Delta Price\ + \beta 6\ \Delta Calories + \varepsilon$$

<u>Table 10. Health Consciousness Effects on Food Characteristic Weights</u>

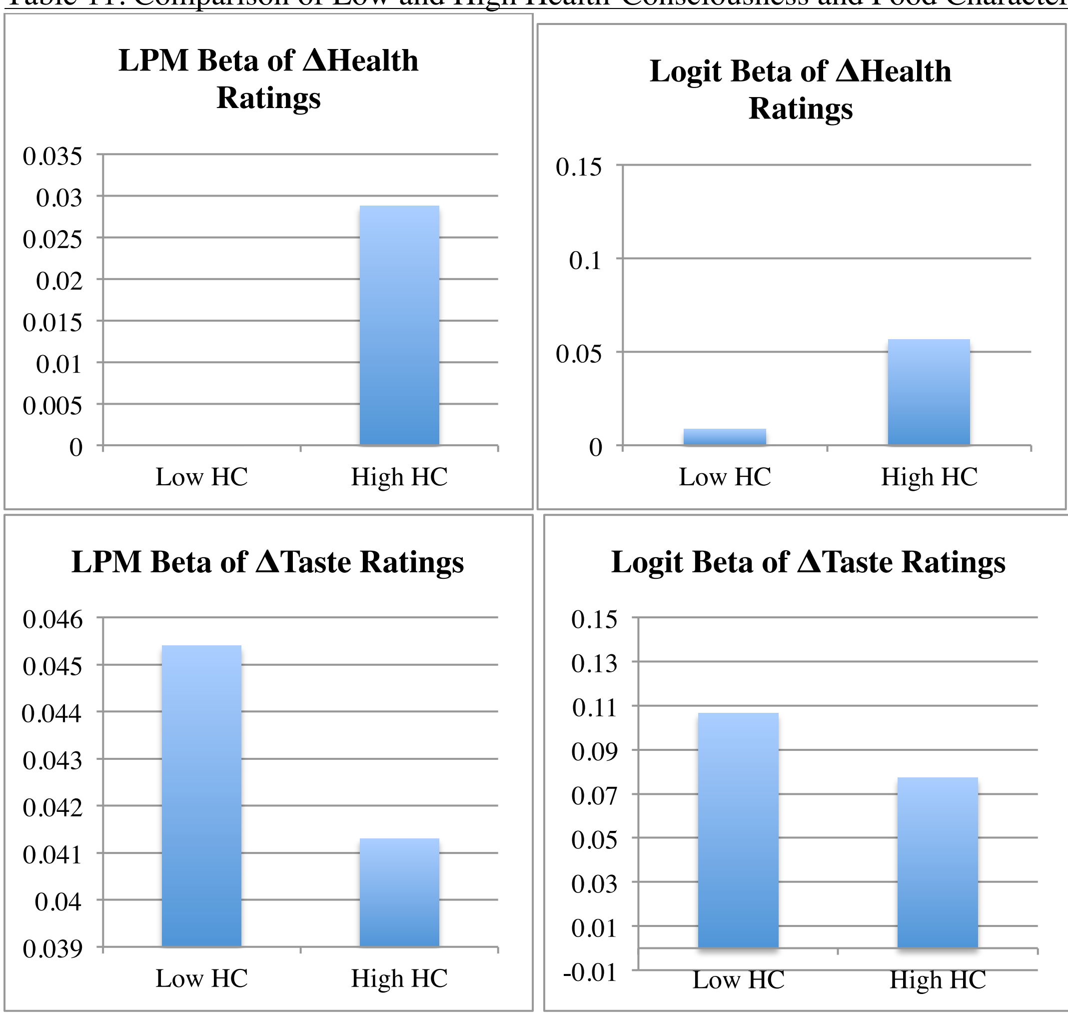
		LPM	**Logistic Model (Marginal Effects)**
Low Health-Consciousness	ΔHealth	0.0000 (.0024)	0.0087 (0.0062)
	ΔTaste	0.0454*** (0.0038)	0.1066*** (0.0092)
	ΔWant	0.1554*** (0.0034)	0.2964*** (0.0097)
	ΔSalience	0.0047 (0.0029)	0.0012 (0.0058)
High Health-Consciousness	ΔHealth	0.0288*** (0.0034)	0.0567*** (0.0069)
	ΔTaste	0.0413*** (0.0055)	0.0774*** (0.0086)
	ΔWant	0.1348*** (0.0046)	0.2437*** (0.0094)
	ΔSalience	0.0090** (0.0040)	0.0159** (0.0065)
	ΔPrice	-0.0278*** (0.0041)	-0.0576*** (0.0076)

ΔCalories	-0.0004*** (0.0000)	-0.0008*** (0.0000)

Note: Standard errors given in parentheses
*p<0.10, **p<0.05, ***p<0.01

Similar to the self-control internal state, in above Table 10, one can see that when participants are separated at the median values of health consciousness, another important internal state involved in food decision-making, there is a significant difference in the weighting of the multiple attributes of the food items. The betas of ΔHealth show a significantly higher weighting of health in the high health consciousness subjects; the betas of ΔTaste and ΔWant are significantly higher for low health-consciousness subjects (respectively: X^2=35.98, P> X^2=0.0000; X^2=5.56, P> X^2=0.0184; X^2=15.22, P> X^2=0.0010). Also of interest, across all subjects, ΔPrice has a negative effect on ChoiceLeft, implying that as an item gets more expensive, people may stray from that choice. These results are illustrated as beta weights in Table 11 below.

Table 11. Comparison of Low and High Health-Consciousness and Food Characteristic Weights

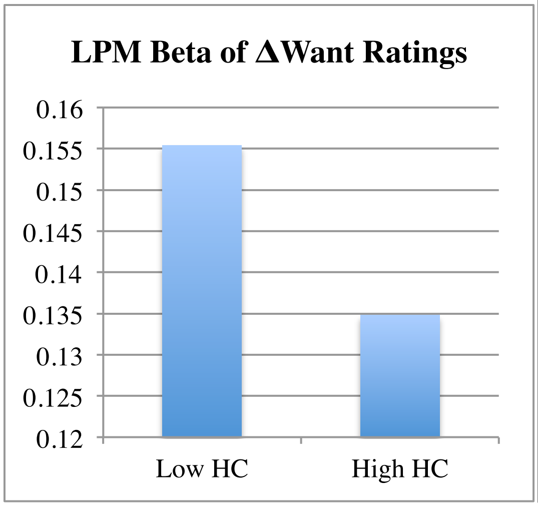


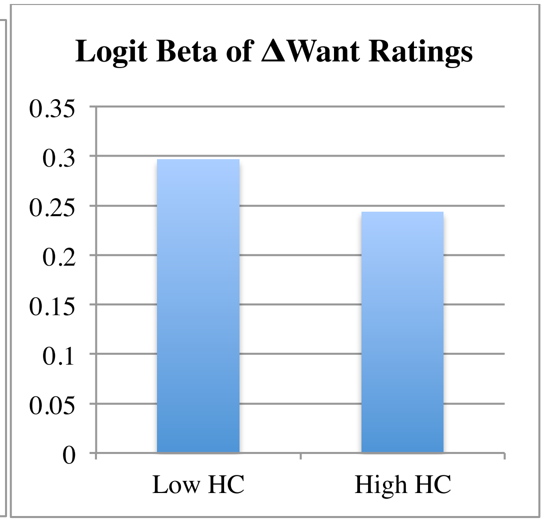
Condition ΔHealth Betas are different:

X^2=35.98
P> X^2=0.0000

Condition ΔTaste Betas are different:

X^2=5.56
P> X^2=0.0184





Condition ΔWant Betas are different:

X^2=15.22
P> X^2=0.001

E. FE Regression Models on Time Effects

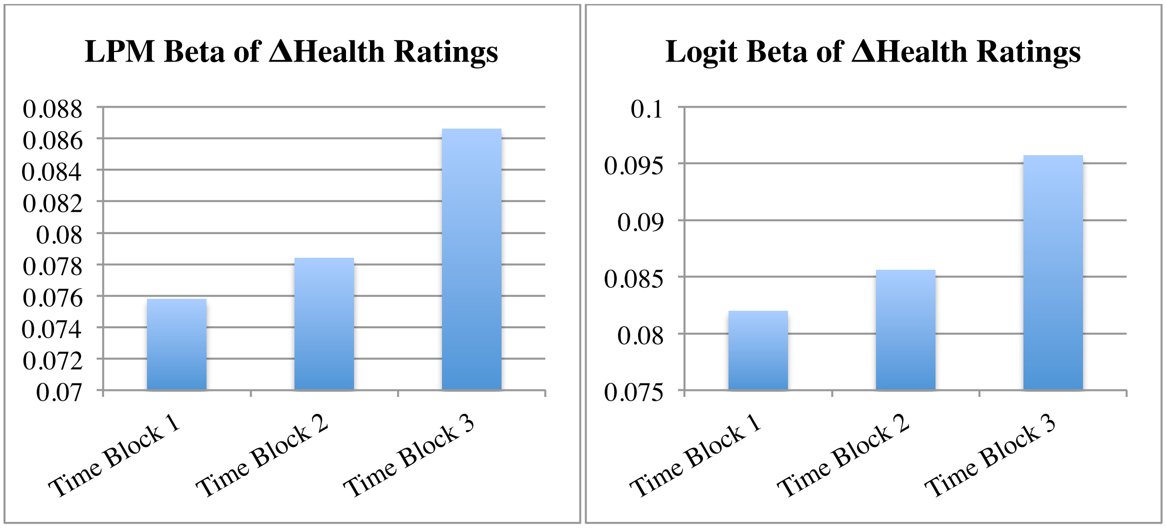
$$ChoiceLeft = (\beta1\ \Delta Health) * TimeBlock + \beta2\ \Delta Price + \beta3\ \Delta Calories\ + \varepsilon$$

Table 12. The Relationship between Time Effects and Health External Cue Effect

	LPM	**Logistic Model (Marginal Effects)**
ΔHealth in Time Block 1	0.0758*** (0.0058)	0.0820* (0.0098)
ΔHealth in Time Block 2	0.0784*** (0.0059)	0.0856*** (0.0135)
ΔHealth in Time Block 3	0.0866*** (0.0061)	0.0957*** (0.0127)
ΔPrice	-0.0203** (-0.0064)	-0.0224*** (0.0074)
ΔCalories	-0.0001* (0.0001)	-0.0001* (0.0001)

Note: Standard errors given in parentheses
*p<0.10, **p<0.05, ***p<0.01

Table 21. The Relationship between Time Effects and Health External Cue Effect



Time ΔHealth Betas are different:

X^2=2.50
P> X^2=0.2868

In these regression models probing for time effects in the health cue condition, one can see that there is no diminished effect of the health prime effect on the ΔHealth beta across the time blocks of the experiment. All three coefficients are significantly different from 0. Directionally, it seems that there is an increasing weight of ΔHealth, but the difference between the ΔHealth betas are not significant at a P>0.10 level.

F. FE Regression Models on Non-Food Choices

When looking at non-food decisions, metrics used were ΔUse, ΔWant, and ΔEnjoy. Omitted were the choices that included the Domino's gift card, which is clearly not a non-food choice. These measure the utility, enjoyment, and desirability of the choices. The regressions of the weights of these characteristics as they interact with the external cue conditions are shown in Table 13 below.

$$ChoiceLeft = (\beta 1\ \Delta Use + \beta 2\ \Delta Want + \beta 3\ \Delta Enjoy) * Prime + \varepsilon$$

Table 13. External Cue Effects on Enjoyment and Utility Weights

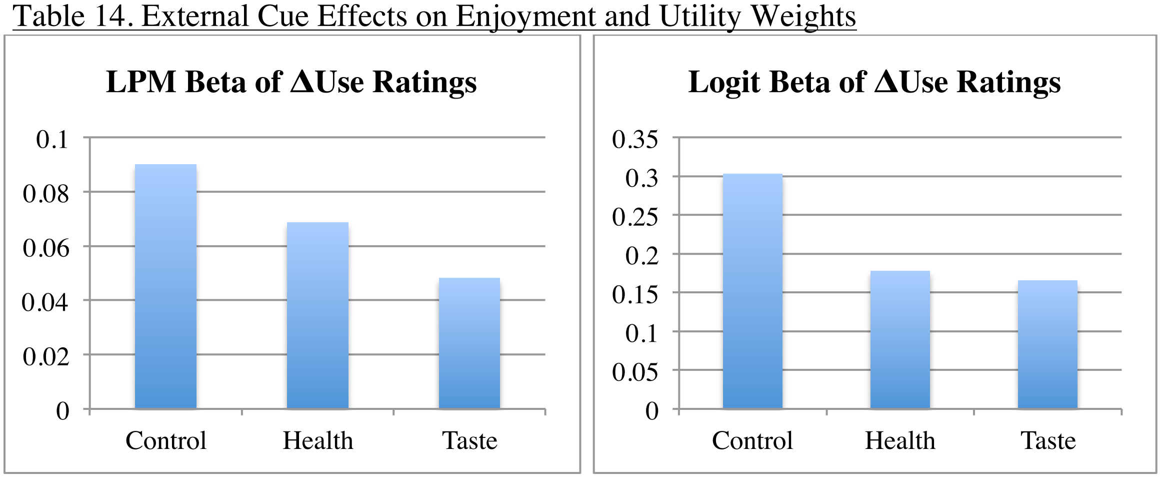
		LPM	Logistic Model (Marginal Effects)
Control Prime	ΔUse	0.0901*** (0.0141)	0.3031*** (0.0476)
	ΔWant	0.0784*** (0.0130)	0.2021*** (0.0429)
	ΔEnjoy	0.0107 (0.0144)	0. 0401 (0.0372)

Health Prime	ΔUse	0.0686*** (0.0127)	0.1777*** (0.0327)
	ΔWant	0.0461*** (0.0132)	0. 124*** (0.0337)
	ΔEnjoy	0.0643*** (0.0134)	0.1721*** (0.0347)
Taste Prime	ΔUse	0.0481** (0.0192)	0.1656** (0.0668)
	ΔWant	0.0516*** (0.0196)	0.1903** (0.0647)
	ΔEnjoy	0.0856*** (0.0209)	0.2645 ** (0.0749)

Note: Standard errors given in parentheses
*p<0.10, **p<0.05, ***p<0.01

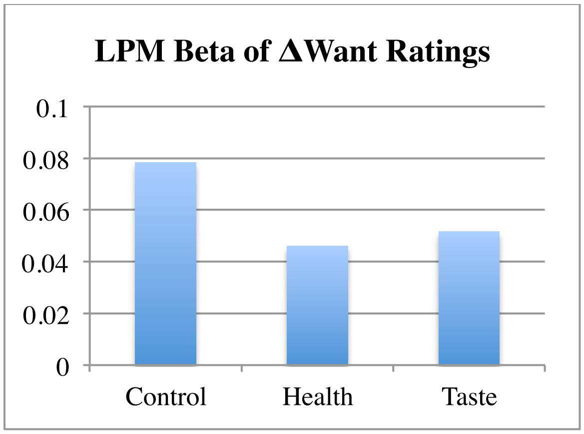
These results show that all the characteristics, ΔUse, ΔWant, and ΔEnjoy, are significant factors across all conditions except for ΔEnjoy in the control prime. The most interesting significant difference across the cues however is the betas of ΔUse and ΔWant (respectively X^2=5.24, P> X^2=0.0729; X^2=10.50, P> X^2=0.0052). The beta of ΔUse is higher in the health condition than in the taste condition, and the beta of ΔWant is higher in the taste condition than in the health condition. This makes it seem as though there is a potential carryover effect of the health and taste external cues, which loosely are equivalent to utility and hedonic pleasure of the non-food choices.

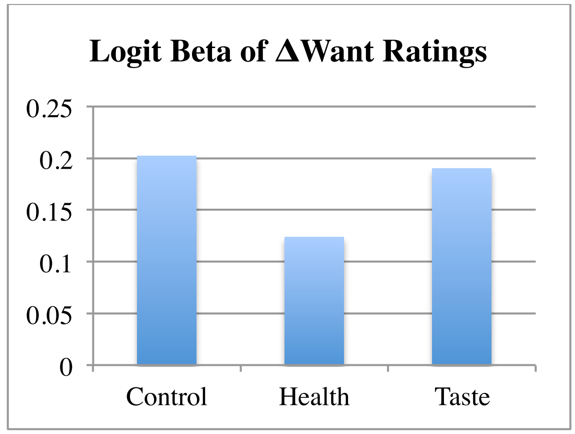
Table 14. External Cue Effects on Enjoyment and Utility Weights



Condition ΔUse Betas are different:

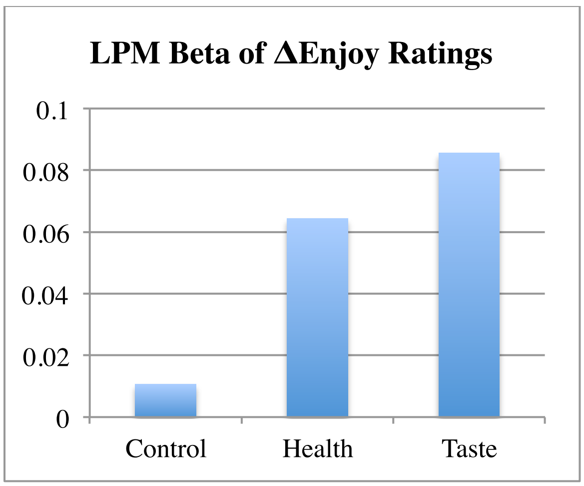
X^2=5.24
P> X^2=0.0729

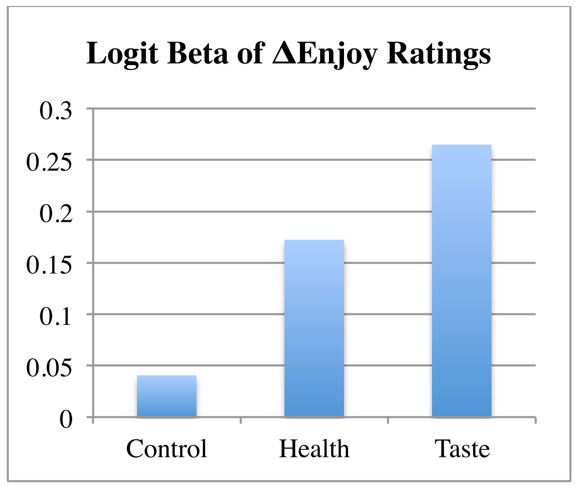




Condition ΔEnjoy Betas are different:

X^2=3.09
P> X^2=0.2133





Condition ΔWant Betas are different:

X^2=10.50
P> X^2=0.0052

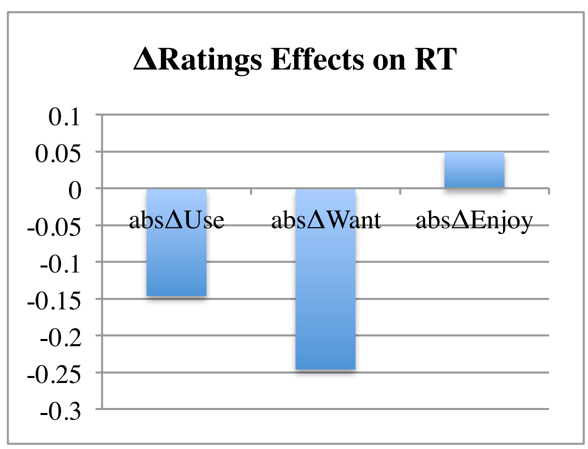
$RT = \beta 1\ abs\Delta Use + \beta 2\ abs\Delta Want + \beta 3\ abs\Delta Enjoy + \varepsilon$

<u>Table 15. Estimates of ΔRatings on RT</u>

<u>Table 16. Comparisons of the Relationship between ΔRatings and RT</u>

	LPM
absΔUse	-0.1460** (0.0488)
absΔWant	-0.2456*** (0.049)
absΔEnjoy	0.0487 (0.0499)

Note: Standard errors given in parentheses
*p<0.10, **p<0.05, ***p<0.01



ΔRatings Betas are different:

F=51.90
P> F=0.0000

To mirror the response time findings in the food decision trials, we regressed the characteristic weights, absΔUse, absΔEnjoy, and absΔWant. The betas for absΔUse and absΔEnjoy are significantly negatively correlated with RT, which follows the logic that the higher the discrepancy in the attribute values, the easier and faster the decision is.

Table 17. Estimates of the Relationship between Self-Control and Weights of ΔRatings

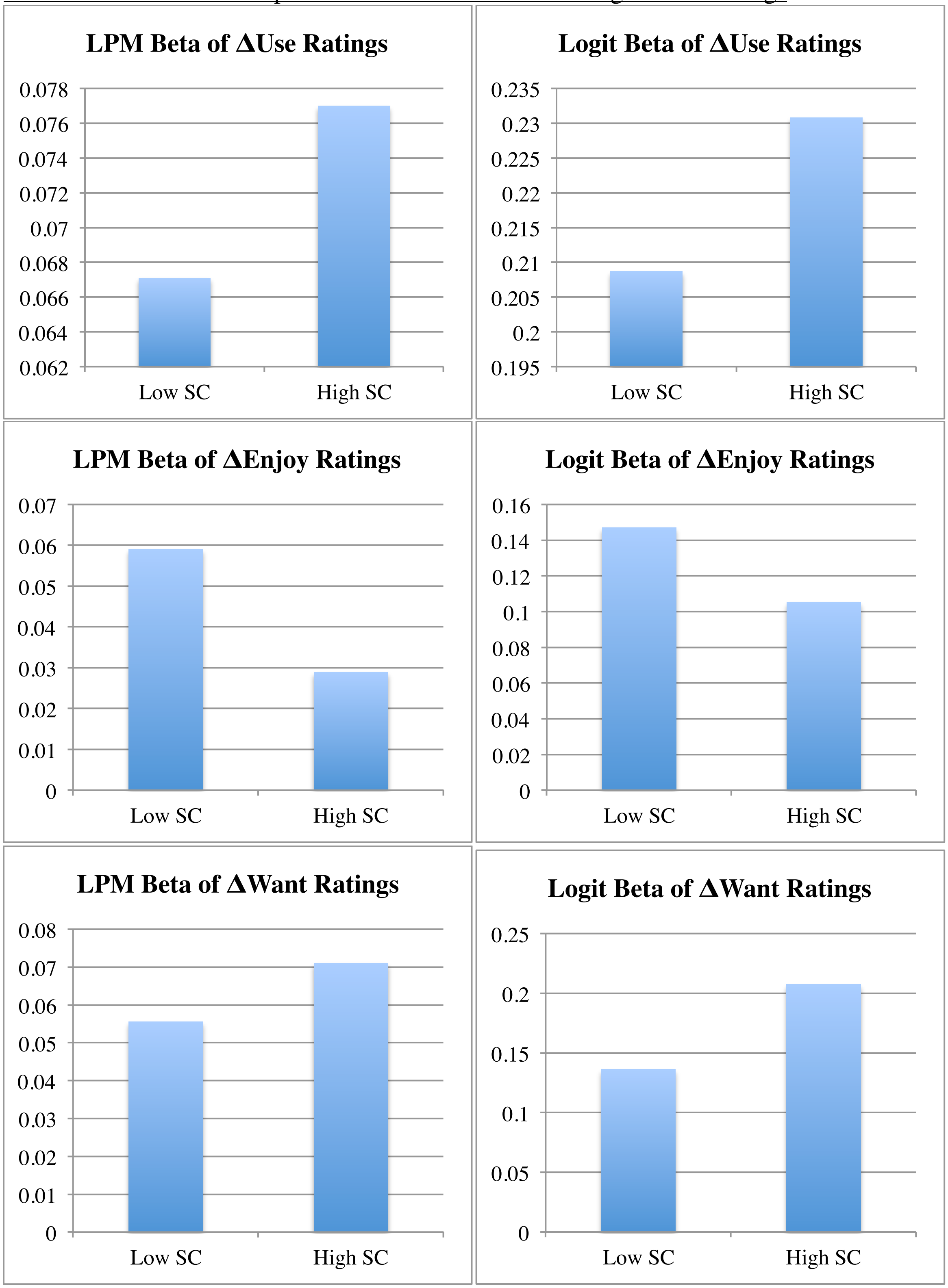
		LPM	**Logistic Model (Marginal Effects)**
Low Self-Control	ΔUse	0.0671*** (0.0108)	0.2087*** (0.0311)
	ΔEnjoy	0.0591*** (0.0110)	0.1470*** (0.0287)
	ΔWant	0.0556*** (0.0101)	0.1362*** (0.0292)
High Self-Control	ΔUse	0.0770*** (0.0137)	0.2308*** (0.0417)
	ΔEnjoy	0.0289** (0.0150)	0.1052*** (0.0400)
	ΔWant	0.0710*** (0.0148)	0.2074*** (0.0443)

Note: Standard errors given in parentheses
*p<0.10, **p<0.05, ***p<0.01

When looking at the internal state self-control's relationship with enjoyment and utility weights on non-food choices, we see that none of the differences between weights are significant between low and high self-control subjects. However, looking at directionality, one can observe that ΔUse betas are higher in high self-control subjects than in low self-control subjects, and ΔEnjoy betas are higher in low self-control subjects than in high self-control subjects. Interestingly, ΔWant betas are higher in high self-control subjects than in low self-control subjects, implying that those who self-report as having high self-control weight wanting an item more – a possible explanation being that these subjects think of high utility as high wanting. These patterns can be seen more easily in Table 18 on the next page.

$$ChoiceLeft = (\beta 1\ \Delta Use + \beta 2\ \Delta Want + \beta 3\ \Delta Enjoy) * SC + \varepsilon$$
$$ChoiceLeft = (\beta 1\ \Delta Use + \beta 2\ \Delta Want + \beta 3\ \Delta Enjoy) * HC + \varepsilon$$

Table 18. The Relationship between Self-Control and Weights of ΔRatings



SC ΔUse Betas are different:

X^2=0.18
P> X^2=0.6715

SC ΔEnjoy Betas are different:

X^2=0.72
P> X^2=0.3950

SC ΔWant Betas are different:

X^2=1.80
P> X^2=0.1798

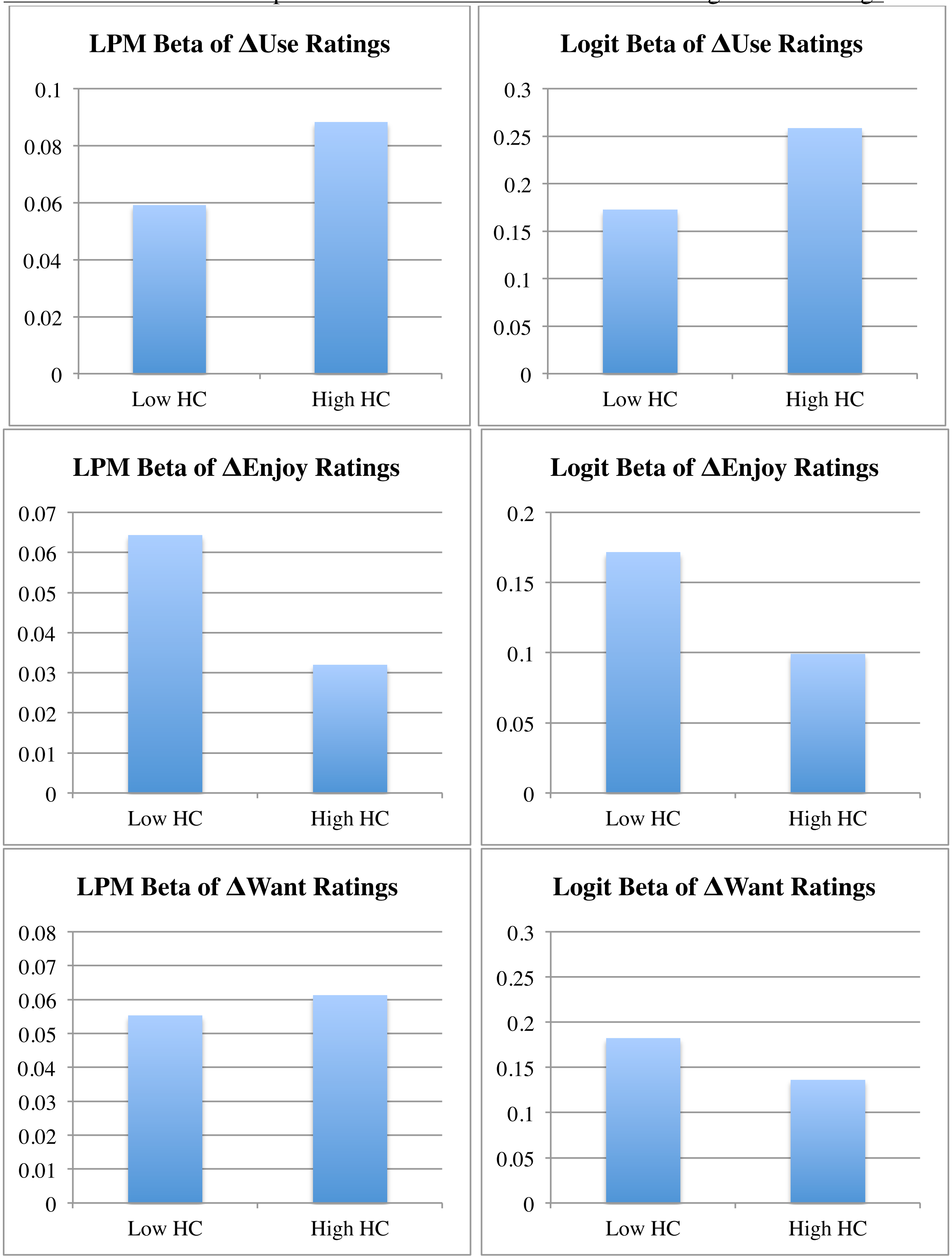
Table 19. Estimates of the Relationship between Health Consciousness and Weights of ΔRatings

		LPM	**Logistic Model (Marginal Effects)**
Low Health Consciousness	ΔUse	0.0591*** (0.0122)	0.1726*** (0.0378)
	ΔEnjoy	0.0643*** (0.0110)	0.1715*** (0.0341)
	ΔWant	0.0553** (0.0128)	0.1823*** (0.0358)
High Health Consciousness	ΔUse	0.0882*** (0.0117)	0.2581*** (0.0318)
	ΔEnjoy	0.0319*** (0.0132)	0.0990*** (0.0361)
	ΔWant	0.0612*** (0.0124)	0.1360*** (0.0308)

Note: Standard errors given in parentheses
*p<0.10, **p<0.05, ***p<0.01

When looking at the internal state health consciousness' relationship with enjoyment and utility weights on non-food choices, we would expect to see little effect. The ΔEnjoy and ΔWant betas are not significantly different between high and low health-consciousness subjects than in high self-control subjects. Interestingly, ΔUse betas are significantly higher (at $p<0.10$ level) in high health consciousness subjects than in low health consciousness subjects, implying that health consciousness is likely correlated with those who look to maximize utility over hedonic enjoyment. Directionally, those with low health consciousness weighed ΔEnjoy more than those with high health consciousness, supporting the opposite side of this claim.

Table 20. The Relationship between Health Consciousness and Weights of ΔRatings



HC ΔUse Betas are different:

X^2=2.97
P> X^2=0.0851

HC ΔEnjoy Betas are different:

X^2=2.37
P> X^2=0.1239

HC ΔWant Betas are different:

X^2=0.88
P> X^2=0.3487

Looking at the regression models in total, it is clear that external cues play a strong role in the weighting of different characteristics of food choices in the decision process, especially effective was the external influence to think about health. This showed significant upswings in influence in health ratings on the choices made, and these effects did not diminish over the course of the behavioral task, when looking at time effects. Interestingly, there were some potential carryover effects into the nonfood choice task, where those who were shown the health external cue were weighting utility heavier than in the taste condition, and want (a hedonic metric) was weighted heavier in the taste condition than in the health condition.

In the regression models looking at visual salience (or at least the measure of salience utilized by this project), we were unable to parse out a significant effect Looking at internal states like self-control and health-consciousness showed that even when collapsing across external cues, those who self report as higher self-control and health-consciousness tend to choose healthier food items, weighting the health aspect more heavily in their decision processes, as well as more high utility non-food items.

II. Drift Diffusion Models

The drift diffusion model (DDM) supplements the traditional regression modeling because it provides highly accurate descriptions of probability of choice using response time and eye-tracking metrics. In the regression models shown in the previous section, we only regressed ChoiceLeft on the various independent variables or regressed reaction time on the various independent variables. With DDM, we can take into account both simultaneously, providing quantitative explanations of the psychometrics, chronometrics, and neurometrics of binary choice (Krajbich & Rangel, 2011).

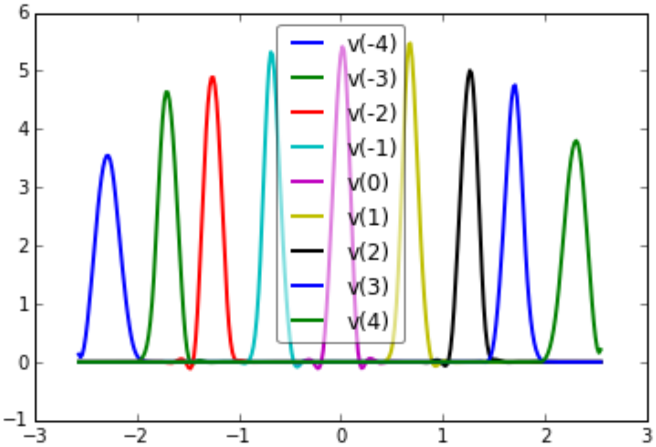
Using the Python HDDM toolbox, we were able to run hierarchical Bayesian estimations of the drift-diffusion model (Wieki et al., 2013). The drift diffusion model is a tool used to illustrate "latent psychological processes underlying decision making" (Wieki et al, 2013). The particular simulation method we used to derive this model is the hierarchical Bayesian parameter estimation. Bayesian data analytic methods are becoming more commonplace in cognitive sciences because it allows for inference of the full posterior distribution of the estimated parameters, quantifying uncertainty in the estimation. The hierarchical Bayesian method allows for group and subject parameters to be estimated simultaneously at different levels: subject parameters are drawn from the group distribution, taking into account that subjects have individual preferences or biases, but are also similar to each other in regards to the general group patterns. The particular method used for this project is called HDDM, which requires less data per subject/condition than the non-hierarchical method and can handle outliers in the data, which can be common in cognitive data including that of eye-tracking.

It is the drift rate parameter (v) that will be the primary concern for this paper. The graphs in the following results section show the posterior distributions of the drift rate (v) – positive for left choice, negative for right choice – of the subsets of observations in an effort to compare said subsets to illustrate effects of various aspects of the decision-making process.

A. Drift Diffusion Models Exploring Effects of External Cues

First, to confirm that the drift rates go in ascending order as the difference in want rating becomes larger, we ran the data through HDDM binning ΔWant. As you can see in Graph 1 below, it follows as expected from ΔWant= 4 down to ΔWant= -4, from highest drift rate (v) to lowest drift rate (v).

Graph 1. Overall DDM for ΔWants

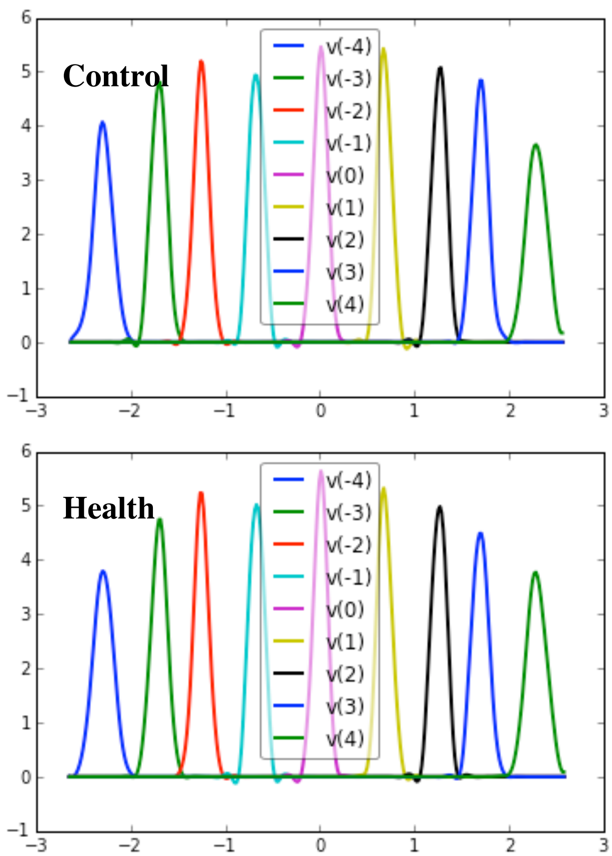


Legend:
Blue$_1$ = ΔWant of -4
Green$_1$ = ΔWant of -3
Red = ΔWant of -2
Aqua = ΔWant of -1
Pink = ΔWant of 0
Yellow = ΔWant of 1
Black = ΔWant of 2
Blue$_2$ = ΔWant of 3
Green$_2$ = ΔWant of 4

Note: There are two blues and greens because the HDDM package inherently only has 7 unique colors.

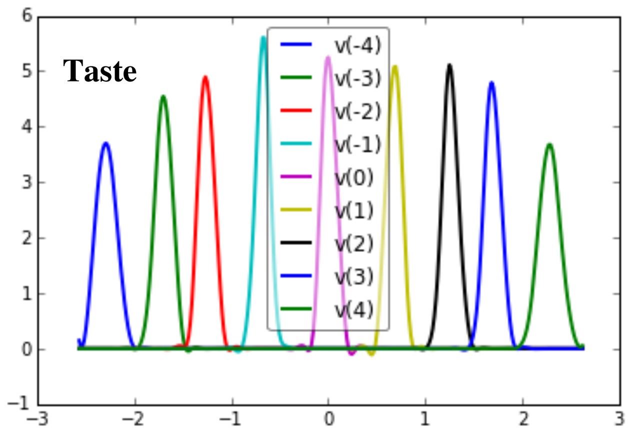
Then to look at the difference in drift diffusion across the external cues, we ran simulations in each condition subset. As you can see in Graph 2, though we expected to see some difference in the health condition, perhaps slower drift rate for the extreme ΔWant bins due to conflicting health and want rates, but it does not seem it drastically affects ΔWant bin drift rates.

Graph 2. Food Decision DDMs for ΔWants for External Cues



Legend:
Blue$_1$ = ΔWant of -4
Green$_1$ = ΔWant of -3
Red = ΔWant of -2
Aqua = ΔWant of -1
Pink = ΔWant of 0
Yellow = ΔWant of 1
Black = ΔWant of 2
Blue$_2$ = ΔWant of 3
Green$_2$ = ΔWant of 4

Note: There are two blues and greens because the HDDM package inherently only has 7 unique colors.

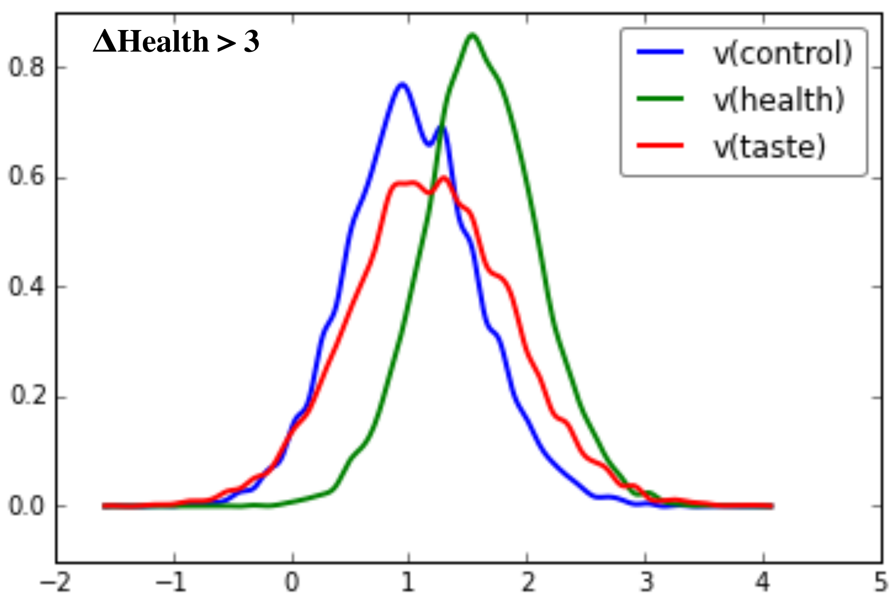


Legend:
Blue$_1$ = ΔWant of -4
Green$_1$ = ΔWant of -3
Red = ΔWant of -2
Aqua = ΔWant of -1
Pink = ΔWant of 0
Yellow = ΔWant of 1
Black = ΔWant of 2
Blue$_2$ = ΔWant of 3
Green$_2$ = ΔWant of 4

Note: There are two blues and greens because the HDDM package inherently only has 7 unique colors.

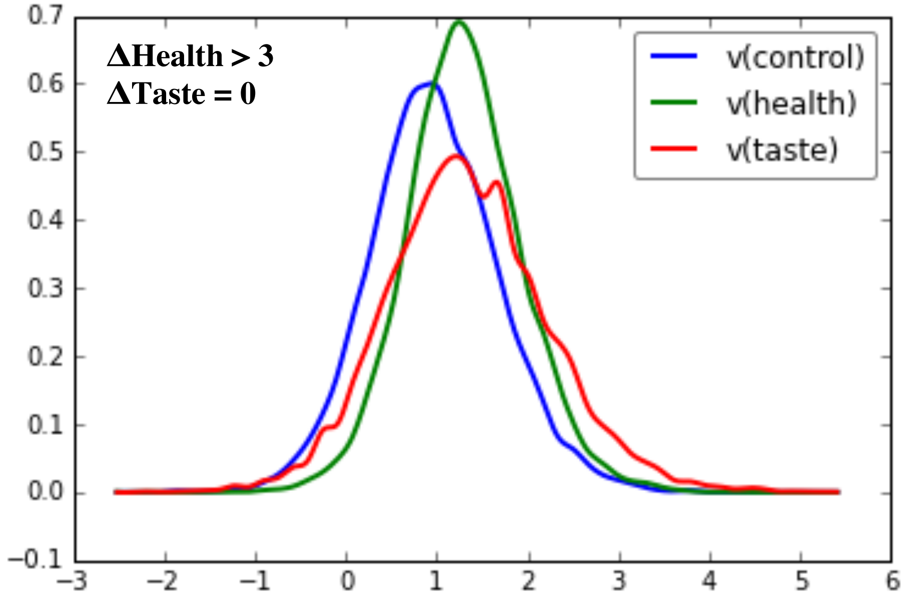
Then to explore drift rates when there were large discrepancies in certain values, we ran simulations to determine DDMs for when ΔHealth > 3 and when ΔTaste > 3. As you can see below, for the first case, it seems as though the health external cue quickens the decisions, as its drift rate distribution is further right than that of both the taste and control condition.

Graph 3.A. Food Decision DDM for External Cues when ΔHealth > 3



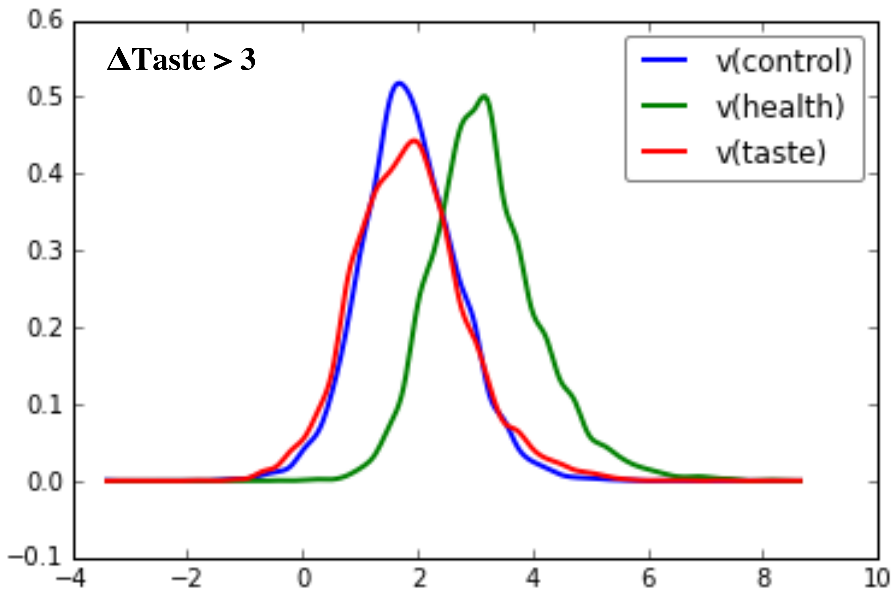
When we also held ΔTaste = 0, a similar pattern is found, but a clear gap between the health external cue and the other two conditions was not seen, which one would expect. See in Graph 3.B. on following page.

Graph 3.B. Food Decision DDM for External Cues when ΔHealth > 3



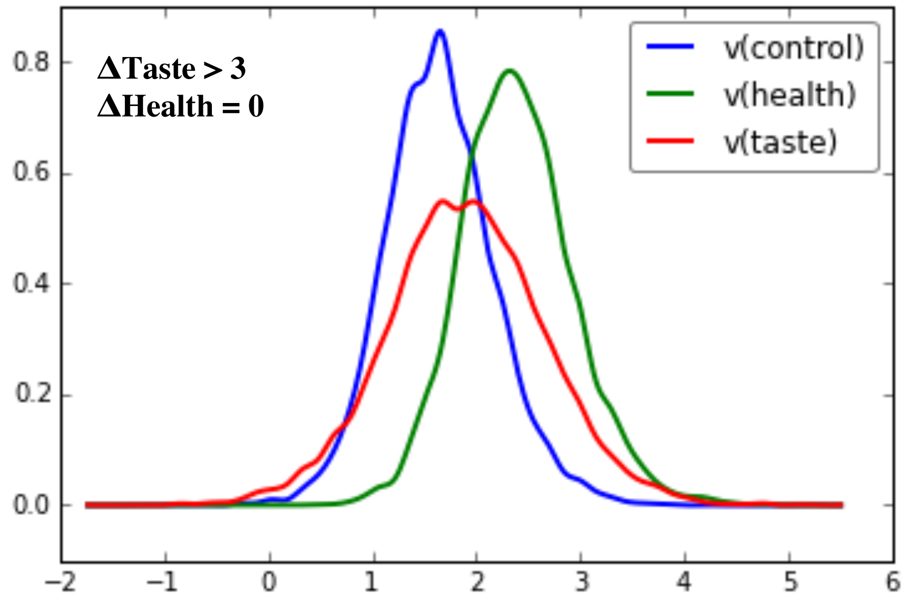
Interestingly, when ran for ΔTaste > 3, we do not see a switch in the drift rate order of the conditions. Namely, the health external cue condition still has the highest drift rate. This seems to imply that no matter the external cue, when taste discrepancy is high, choices are made quickly towards the tastier item. You can see that the peaks have been shifted over to the right significantly further than in the ΔHealth > 3 simulations. Taste seems to have a stronger effect on decisions regardless of external cuing.

Graph 4. A. Food Decision DDM for External Cues when ΔTaste > 3



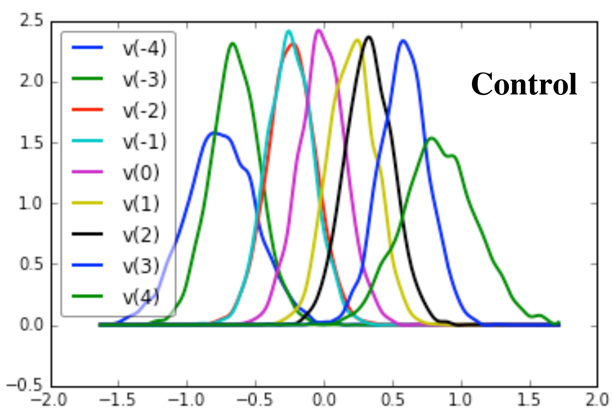
Same pattern is observed when we held ΔHealth = 0, as seen in the next Graph 4.B.

Graph 4. B. Food Decision DDM for External Cues when ΔTaste > 3 and ΔHealth = 0.



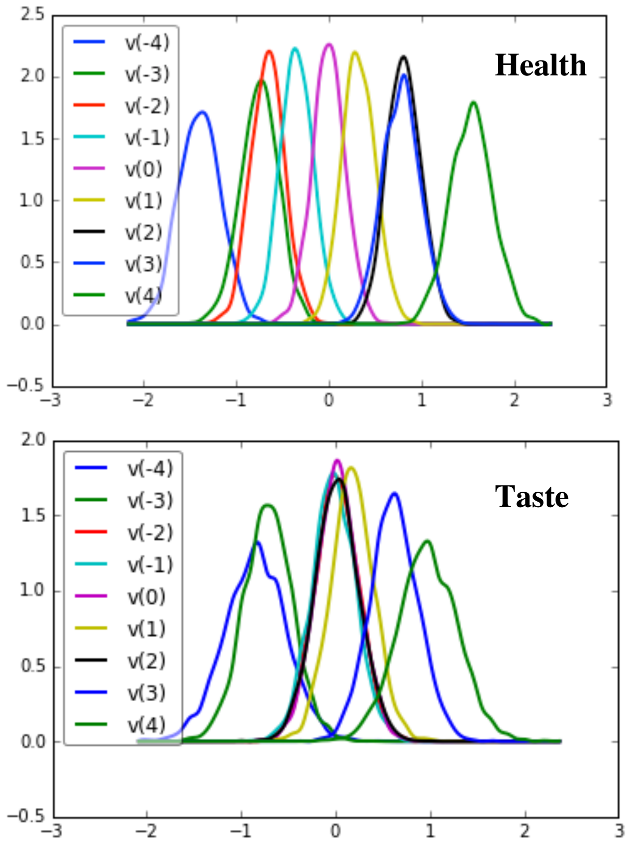
When the data was binned by ΔHealth and ran simulations for each external cue condition, it is clear that for in the health cue condition, the extreme ΔHealth peaks are the sharpest, meaning that those drift rates are the most consistent, thus are confidently quicker choices.

Graph 5. Food Decision DDM for ΔHealths for External Cues



Legend:
Blue$_1$ = ΔHealth of -4
Green$_1$ = ΔHealth of -3
Red = ΔHealth of -2
Aqua = ΔHealth of -1
Pink = ΔHealth of 0
Yellow = ΔHealth of 1
Black = ΔHealth of 2
Blue$_2$ = ΔHealth of 3
Green$_2$ = ΔHealth of 4

Note: There are two blues and greens because the HDDM package inherently only has 7 unique colors.



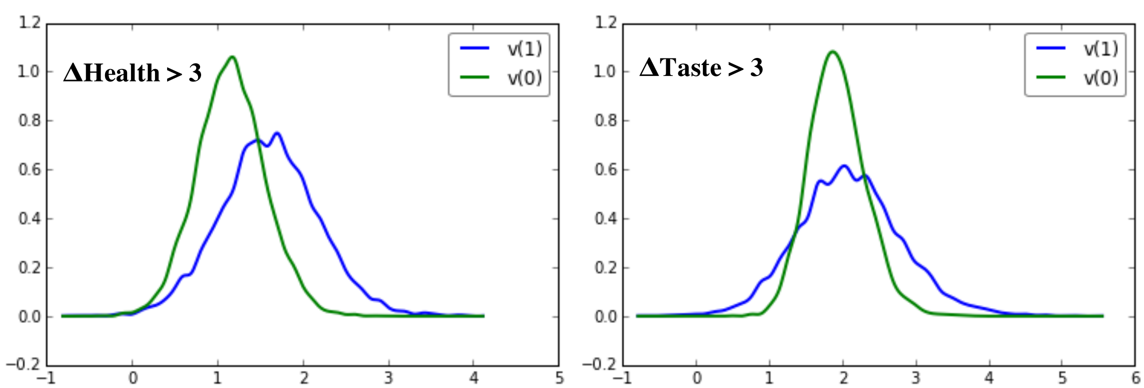
Legend:
Blue_1 = ΔHealth of -4
Green_1 = ΔHealth of -3
Red = ΔHealth of -2
Aqua = ΔHealth of -1
Pink = ΔHealth of 0
Yellow = ΔHealth of 1
Black = ΔHealth of 2
Blue_2 = ΔHealth of 3
Green_2 = ΔHealth of 4

Note: There are two blues and greens because the HDDM package inherently only has 7 unique colors.

B. INTERNAL STATES:

Drift diffusion models were also generated for the internal states: self-control and health consciousness. See results below in Graph 6.

Graph 6.A. & B.
Low (0) and High (1) Self-Control in Food Decisions with ΔHealth > 3 or ΔTaste > 3



Legend: Green = Low Self-Control (0), Blue = High Self-Control (1)

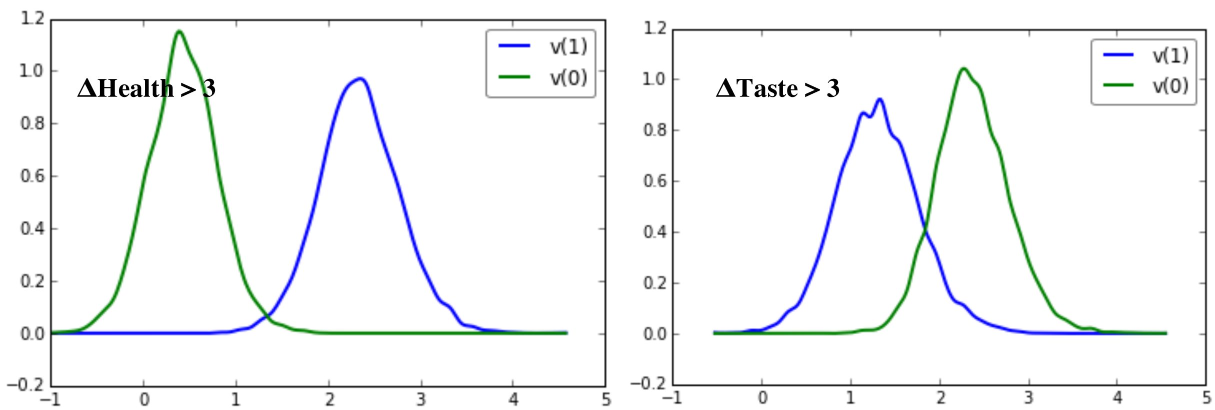
You can see in the above Graph 6.A. that in food choices where ΔHealth > 3, high self-control subjects (blue) have a higher drift rate, implying that they make these choices towards the healthier choice more easily, more quickly. The peak for these high self-control subjects however is fatter, implying that there is more variance in how these subjects make these ΔHealth > 3 decisions.

You can see in the graph to the right, Graph 6.B., that in food choices where ΔTaste > 3, high self-control subjects (blue) and low self-control subjects converge to around the same drift rate, but again, the distribution of high self-control subjects is fatter implying that there is more variance in how these subjects make these ΔTaste > 3 decisions.

You can see in the below Graph 7.A., that in food choices where ΔHealth > 3, high health consciousness subjects (blue) have a much higher drift rate than those in the low health consciousness (green) bin. This reflects that those who are more health conscious are making these decisions towards the healthier item with little conflict during the deliberation process.

Then in the graph to the right, Graph 7.B., one can see that that in food choices where ΔTaste > 3, low health consciousness subjects (green) are making their choices with less conflict and with more speed. The low health consciousness drift rate is significantly higher than that of those with high health consciousness.

Graph 7.A. & B.
Low (0) and High (1) Health Consciousness in Food Decisions with ΔHealth > 3 or ΔTaste > 3



Legend: Green = Low Health-Consciousness (0)**,** Blue = High Health-Consciousness (1)

The opposite drift rate order in the ΔHealth > 3 and ΔTaste > 3 conditions is a clear indication that those who are more health conscious are weighting the health characteristic and the less health conscious are weighting the taste characteristic much more during the multi-attribute value assessment process of food decision-making.

Looking at the drift diffusion models as a whole, the main takeaways are the following: 1) DDM is a novel computational model that is able to create individual subgroup parameters from the enter group distribution, and 2) there are clear differences in the decision processes depending on which of the different external cue conditions as well as different internal state groups the individual is in.

The health external cue quickens the decisions when ΔTaste > 3, as its drift rate distribution is further right than that of both the taste and control condition. Interestingly, when DDMs were created for the external cue conditions for ΔTaste > 3, the drift rates were significantly higher than in the ΔHealth > 3 case. Also, the health external cue condition still had the highest drift rate, implying that no matter the external cue, when taste discrepancy is high, choices are made quickly towards the tastier item.

Supplementing the regression model findings by incorporating reaction time and eye-tracking data, the HDDM finds that compared to those in the control and taste cue conditions, the subgroup in the health cue condition, in choices with the most extreme ΔHealths, show drift rate distributions with the sharpest peaks, meaning that those drift rates are the most consistent, thus are confidently quicker choices. This makes it clear that the health external cue has a significant effect on the health value weighting.

We were also able to observe that high self-control and high health consciousness subjects make quicker, more confident healthy decisions when confronted with large health discrepancy choice sets. In contrast, those with low self-control and health consciousness were more likely to choose the tastier option in high taste discrepancy choice trials.

VI. Conclusion

Food choice is a complicated decision that requires the assessment of conflicting goals and attributes: personal preferences for health and taste as well as personal goals in utility maximizing or satisficing. This project employs two data analysis models: regression models and hierarchical Bayesian drift diffusion models of decision-making. Lab measurements of econometric behavior, eye movement, inherent preferences, visual salience, and explicit cues were combined into a more all-encompassing computational model of the attentional and motivational processes that influence food choice.

It is clear that external cues play a strong role in the weighting of various aspects of food choices in this particular decision process. Especially potent was the external influence to think about health. This showed significant upswings in influence in health ratings on the choices made, and these effects did not diminish over the course of the behavioral task. The decision-making process is special in that nutrition is unable to be assessed precisely. Quality signaling done by the market is crucial – the producers and sellers of food (even if by government intervention) may need to play a role in making nutrition assessment more feasible for consumers via labeling and health information, external cues to healthfulness. Explicit cues to health and taste were definitely a strong influence on the decision process observed in this data.

The measure of salience utilized by this project did not seem to be significant in the decision process, but I maintain that with a more precise metric of visual salience, it would definitely influence decision process in a substantial way. Visual salience is an instinctual heuristic search utilized during many decisions in reality and engages the brain in a bottom-up direction while the internal states, that we measured using the drift diffusion model, engage the brain in conscious value assessment guided by personal preferences.

Overall, this paper shows that many of the neuroscientific methods and data analyses employed in this project can be important to economics. For example, the hierarchical Bayesian drift diffusion model adds depth to the traditional regression modeling by incorporating more variables such as reaction times and eye movements, while also being able to simultaneously create group distributions but then extracting subgroup or participant distributions from the tier above.

The results show that the food decision process deviates from the usual, cut-and-dry utility maximization model. The reality of human decision-making is many times imperfect and malleable (by external cues) utility satisficing that is personalized to each person’s behaviors and preferences (such as levels of self-control and health consciousness). Taking these factors into account with more nuanced computation models is the next step in understanding more complex decision-making and value assessment processes such as those regarding food (Schwartz et al., 2002).

VI. Appendix

A. Cues – Articles: Control, Health, Taste

Control Instructions:

In this study you will see pairs of food items and pairs of non-food items appear on the screen. On each trial, you must choose which item you would like to receive at the end of the experiment. After the experiment is finished, **you will have to eat the food item you chose** on a randomly selected trial. The non-food item you chose on a randomly selected trial will be ordered and mailed to you.

The purpose of this study is to learn about how people make different types of decisions. To assess your individual perceptions of each item, you will be asked to give various ratings of every item you saw in the choice phase.

Health Prime Instructions:

In this study you will see pairs of food items and pairs of non-food items appear on the screen. On each trial, you must choose which item you would like to receive at the end of the experiment. After the experiment is finished, **you will have to eat the food item you chose** on a randomly selected trial. The non-food item you chose on a randomly selected trial will be ordered and mailed to you.

The purpose of this study is to learn about how a food item's healthfulness affects people's choices about what they eat. We are interested in this question because previous research from The Harvard School of Public Health states that eating a healthy diet is very important. They mention that one key benefit of eating healthy is the ability to maintain a healthy body weight, which can reduce the risk for many diseases. The Centers for Disease Control and Prevention state that the top three killers in America are heart disease, cancer and stroke. Chronic diseases develop over time and are the cumulative effects of each eating decision we make in our lives.

The health benefits of eating healthy are quite clear, but we would like to better understand how people incorporate health into their individual food choices. To assess your perception of the healthfulness of each item, you will be asked to rate the healthfulness of every food item you saw in the choice phase. The non-food items in this study serve as a control against the food items.

Taste Prime Instructions:
In this study you will see pairs of food items and pairs of non-food items appear on the screen. On each trial, you must choose which item you would like to receive at the end of the experiment. After the experiment is finished, you will have to eat the food item you chose on a randomly selected trial. The non-food item you chose on a randomly selected trial will be ordered and mailed to you.

The purpose of this study is to learn how taste affects people's choices about the foods they eat. We are interested in this question because food is a central part of human culture, and is thought to be a source of enjoyment, passion, and fulfillment for many. Eating with others also provides an opportunity to share and create memories, and we would like to understand how food choice is affected by flavor and personal satisfaction.

The benefits of eating for enjoyment are clear, but we would like to better understand how people incorporate taste into their individual food choices. To assess your perception of the taste of each item, you will be asked to rate the taste of every food item you saw in the choice phase. The non-food items in this study serve as a control against the food items.

B. Surveys: BIS/BAS, Self-Control Scale, Maximization Scale, Eating Behavior Questionnaire, Health Consciousness Scale, Food Ratings

BIS/BAS (Behavioral Inhibition/Avoidance System) Scale from (Caswell & White, 1994)

Self-Control Scale from (Tangney, Baumeister, & Boone, 2004)

Maximization Scale from (Schwartz et al., 2002)

Eating Behavior Questionnaire from (van Strien et al., 1986)

Health Consciousness Scale adapted from (Gould et al., 1988)
7-point: +3 to −3 strongly agree to strongly disagree scale; higher values indicate greater health consciousness)

1. I reflect about my health a lot
2. I'm very self conscious about my health
3. I'm alert to changes in my health
4. I'm usually aware of my health
5. I take responsibility for the state of my health
6. I'm aware of the state of my health as I go through the day

Example of Food Rating:

SKINNY POP

I have eaten this item.

- Yes
- No

REDUCED FAT POPCORN

1 = Strongly disagree, 7 = Strongly agree

	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
I am familiar with this item							
I am likely to buy this item in the future							
Eating this item is unhealthy							
Eating this item is bad for you							
This item is not nutritious							

C. List of Food Items and Gift Cards

- almonds.jpg
- animals.jpg
- apple.jpg
- applechips.jpg
- banana.jpg
- cheetos.jpg
- chewybar.jpg
- doritos.jpg
- edamame.jpg
- fignewtons.jpg
- goldfish.jpg
- gummys.jpg
- kitkat.jpg
- lays.jpg
- naturevalley.jpg
- orange.jpg
- oreos.jpg
- pbcrackers.jpg
- pistachios.jpg
- popchips.jpg
- popcorn.jpg
- pretzels.jpg
- snickers.jpg
- sunseeds.jpg
- trailmix.jpg

- amc.jpg
- bn.jpg
- cvs.jpg
- dominos.jpg ←
- faa.jpg
- itunes.jpg
- jiffylube.jpg
- redbox.jpg
- staples.jpg
- stubhub.jpg
- target.jpg
- walmart.jpg

Dominos choice omitted for data analysis, as it is not a true non-food item.

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