Judgment and Decision Making, Vol. 11, No. 5, September 2016, pp. 460–471

Salient nutrition labels increase the integration of health attributes in food decision-making

Laura Enax[*] Ian Krajbich[†] Bernd Weber[‡]

Abstract

Every day, people struggle to make healthy eating decisions. Nutrition labels have been used to help people properly balance the tradeoff between healthiness and taste, but research suggests that these labels vary in their effectiveness. Here, we investigated the cognitive mechanism underlying value-based decisions with nutrition labels as modulators of value.

More specifically, we used a binary decision task between products along with two different nutrition labels to examine how salient, color-coded labels, compared to purely information-based labels, alter the choice process. Using drift-diffusion modeling, we investigated whether color-coded labels alter the valuation process, or whether they induce a simple stimulus-response association consistent with the traffic-light colors irrespective of the features of the item, which would manifest in a starting point bias in the model. We show that color-coded labels significantly increased healthy choices by increasing the rate of preference formation (drift rate) towards healthier options without altering the starting point. Salient labels increased the sensitivity to health and decreased the weight on taste, indicating that the integration of health and taste attributes during the choice process is sensitive to how information is displayed. Salient labels proved to be more effective in altering the valuation process towards healthier, goal-directed decisions.

Keywords: nutrition labels, decision-making, diffusion model, drift rate, value-based decision making

1 Introduction

Dietary choice has been a focal interest in many areas of research. Many people struggle to find the correct balance between taste and health considerations in these routine decisions. Goal-directed decision-making requires the decision maker to value each option based on relevant factors such as hunger state and health goals (Rangel, 2013). Previous studies have shown that external cues are important determinants of product valuation and choice (Borgmeier & Westenhoefer, 2009; Bruce et al., 2014; Enax, Weber et al., 2015; Enax et al., 2015; Fernqvist & Ekelund Axelson, 2013; Hübl & Trifts, 2000; Moser et al., 2011; Thaler & Sunstein, 2008; Trudel & Murray, 2011). In the realm of dietary choice, nutrition information labels have been intensively studied, as they serve a decisive role in conveying health attributes of a product (Sonnenberg et al., 2013; Temple & Fraser, 2014) and are important cornerstones of successful public policy interventions (Hawkes et al., 2015). Nutrition labels are perceived as highly credible and are used to guide food selections (Campos et al., 2011), especially when a food's healthfulness is ambiguous (Graham & Jeffery, 2012). Providing health information has been shown to increase hedonic liking ratings of products (Annett et al., 2008; Sabbe et al., 2009), however, other studies provide opposing evidence (Ng et al., 2011; Raghunathan et al., 2006; Wansink & Chandon, 2006). A systematic literature review concluded that consumers can more easily interpret and select healthier choices when confronted with front-of-package labels that incorporate text as well as symbolic color to indicate nutrient levels rather than labels that only include numeric information (Hersey et al., 2013). While consumer interest in nutrition information on foods is high (Grunert & Wills, 2007), the actual use of nutrition labels in real-world settings is more ambiguous, and gaps between reported and actual use are likely (Cowburn & Stockley, 2005; Gorton et al., 2009; Grunert et al., 2010). Nutrition label use varies between product types, socioeconomic status, education, and demographic characteristics (Graham & Jeffery, 2012). Further, the visual saliency of the label itself influences label use, with higher saliency leading to increased fixation likelihood (Graham et al., 2012; Orquin et al., 2012).

When comparing color-coded traffic light (TL) labels directly with other labeling methods, TL labels scored higher in terms of enabling the identification (Borgmeier & West-

Bernd Weber was supported by a Heisenberg Grant (DFG We 4427/3–2). Laura Enax was funded by the BMBF excellence cluster Diet-BB (01EA1410A). Ian Krajbich was funded by NSF Career Grant (1554837).

[*]Department of Epileptology, University Hospital Bonn, Bonn, Germany; Department of NeuroCognition/Imaging, Life & Brain Center, Bonn, Germany; Center for Economics and Neuroscience, Nachtigallenweg 86, 53127 Bonn, Germany. E-mail: Laura.enax@mailbox.org.

[†]Department of Psychology, Department of Economics, The Ohio State University, USA.

[‡]Department of Epileptology, University Hospital Bonn, Bonn, Germany; Department of NeuroCognition/Imaging, Life & Brain Center, Bonn, Germany; Center for Economics and Neuroscience, University of Bonn, Germany

enhoefer, 2009; Gorton et al., 2009; Hawley et al., 2013; Jones & Richardson, 2007; Kelly et al., 2009; Roberto et al., 2012) and selection (Thorndike et al., 2012; van Herpen & Trijp, 2011) of healthier food items, possibly by prompting individuals to consider the health costs of products more strongly (Sonnenberg et al., 2013; Trudel et al., 2015). Importantly, consumers' health evaluations of products have been shown to predict consumption (Trudel et al., 2015). Critically, TL labeling has been shown to increase sales of healthy items and decrease sales of unhealthy items in longitudinal field studies, across socioeconomic status and ethnicity (Levy et al., 2012; Sonnenberg et al., 2013; Thorndike et al., 2012).

While this evidence suggests that TL labeling is effective for increasing health considerations, it still remains unclear exactly how this is occurring. It is important to understand how these labels are changing people's behavior, in order to develop even better interventions and to address similar problems in other domains. However, it is difficult to draw conclusions about the cognitive mechanisms underlying decisions using only choice data (Helfer & Shultz, 2014) because there are often multiple theories that can accommodate the same choice results, but that make different predictions about other measures. Therefore, researchers have begun to study the mechanism by which TL labels influence food choice. For example, TL labels may attract more attention and thus receive more weight in the choice process (Fehr & Rangel, 2011; Hare et al., 2011) similar to how salient smoking warnings are more effective at reducing smoking (Borland et al., 2009). Indeed, a recent eye-tracking study revealed that the use of colors in nutrient-specific labels increases attention to the labels, which are thus more salient, compared to monochromatic labels (Becker et al., 2015). Critically, attention has been shown to mediate the effect of nutrition labels on choice (Bialkova et al., 2014). Other research using a functional magnetic resonance imaging (fMRI) study has shown that TL labels seem to enhance the coupling between brain regions associated with valuation and self-control (Enax, Hu et al., 2015).

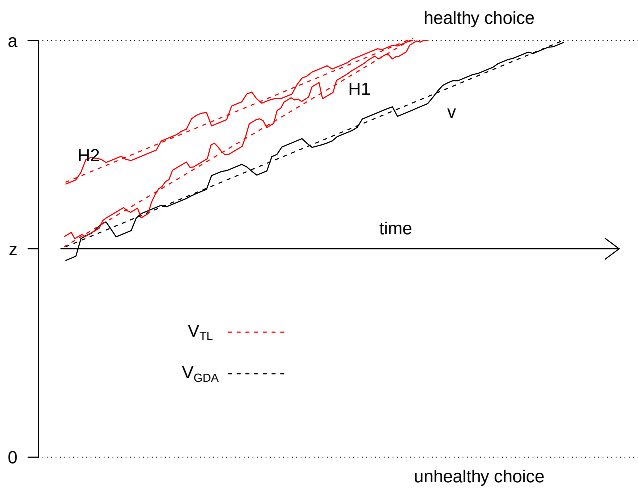
What this previous work leaves unanswered, is how exactly health information and taste preferences are integrated in the choice process, and how the comparison process between items is influenced by the more salient TL display of information. A choice bias could reflect that the healthiness of the items is considered throughout the choice process, a single thought of "I should choose the healthier item", or a response bias caused by, perhaps, an experimenter demand effect. It would be difficult to distinguish between these explanations with just choice behavior, but with response-time (RT) data we can do exactly that. Inspired by computational simulations of the choice process in decisions between food items along with nutrition labels (Helfer & Shultz, 2014), we chose to actually study choice and RT data using a drift diffusion model (DDM) of the choice process. The DDM decomposes choice and RT data into psychologically meaningful parameters, which can be used to infer cognitive processes (Voss et al., 2013) such as response caution, response bias, and noise.

Recent modeling of binary choice experiments has suggested that decisions are formed by the continuous accumulation of evidence towards one of two decision thresholds, which is consistent with the framework of sequential sampling models such as the DDM (Bogacz, 2007; Busemeyer & Townsend, 1993; Ratcliff, 1978). The DDM assumes that information is sampled continuously until sufficient evidence is accumulated for one of the available options, relative to the other. In detail, the information sampling is described by a Wiener Diffusion Process characterized by a constant rate of evidence accumulation (i.e., drift) towards one of two boundaries, combined with Gaussian noise (Ratcliff & Smith, 2004). While DDMs have been traditionally applied in perceptual decision-making, recent studies have used evidence accumulation models to also analyze value-based decisions (Busemeyer & Townsend, 1993; De Martino et al., 2013; Krajbich et al., 2010). Research suggests that using RTs, in addition to choice data, can improve predictions of subjects' preferences and shed light on the mechanism how different attributes are incorporated in the decision (Krajbich et al., 2014; Taubinsky et al., 2009). The stochasticity in value-based decision-making is thought to arise, at least in part, from the noise in how our brain represents the choice options (Krajbich et al., 2014).

Here we build on previous applications of DDM to food choice by Krajbich, Rangel, and colleagues. In that work they study how people choose between food items based on independently collected "liking ratings" on a simple Likert scale. They assume that in value-based decisions, the decision makers cannot immediately access their preferences for each option, but slowly determine their preferences by accumulating and comparing evidence for the options until a predetermined level of confidence is reached. As before, this evidence accumulation process is modeled as Wiener diffusion of a net evidence variable, referred to as the relative decision value (RDV). Importantly, the average rate of evidence accumulation depends on the underlying subjective value difference of the two options, and is in our case dependent on the sensitivity to health and the weight on taste attributes.

To investigate the relative effects of health and taste concerns, we follow the approach used by Philiastides and Ratcliff (2013) who investigated the effects of brand labels on clothing choice. In that work, the authors assumed that the binary relative quality of the brand label (better vs. worse) would influence the rate of evidence accumulation of the items (lower for the worse brand, higher for the better brand). By analogy, here we assumed that the binary relative quality of the nutritional content (healthier vs. unhealthier)

Figure 1: Graphical representation of the diffusion model parameters for a binary choice between healthy and unhealthy products, labeled with either a numeric GDA or a salient TL label. We tested whether salient TL labels increase the drift rate towards the healthy options (H1, slope for TL steeper than for GDA). Alternatively, it is conceivable that TL labeling induces a starting point bias (by shifting the parameter z up or down but with the same slope of the drift rate, H2). Note that, for simplification, the non-decision time parameter is not depicted in this figure. Abbreviations used in the Figure: v, mean drift rate; a, boundary between the two responses; z, starting point; TL, traffic light; GDA, guideline daily amount.



would influence the rate of evidence accumulation of the foods.

We tested the influence of two different nutrition labels, that is, a color-coded, and thereby more salient (Becker et al., 2015), TL label and a purely information-based, guideline daily amount (GDA) label. Both labels are similar in size, have been compared in previous studies (Gorton et al., 2009; Hamlin et al., 2015; Jones & Richardson, 2007; Maubach & Hoek, 2008; Savoie et al., 2013), and are preferred over very simplified health information, such as health logos (Grunert & Wills, 2007). Based on previous studies (e.g., Thorndike et al., 2012; van Herpen & Trijp, 2011), we predicted that color-coded nutrition labels would increase healthy choices in a binary choice task. We then used the DDM to analyze the underlying choice process. If the nutrition information directly influences subjects' preferences, this should be seen as changes in drift rate, but not in starting point biases or non-decision time (Philiastides & Ratcliff, 2013), see Figure 1 (H1). An alternative hypothesis is that the salient TL labels might simply produce a stimulus-response association, irrespective of the items' features. This would manifest as a bias in the starting point of the choice process, that is, a bias towards the decision threshold for the healthier item (H2). Further, we expect that salient nutrition labels decrease the weight on taste attributes and increase the sensitivity to health features.

2 Method

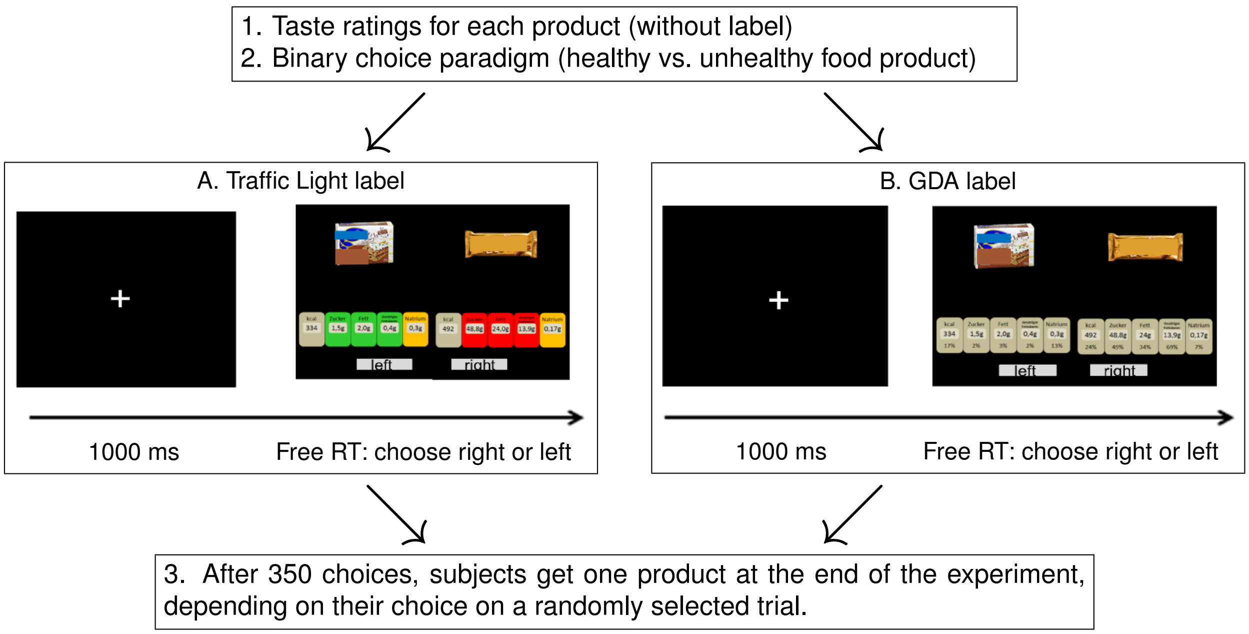
2.1 Subjects

44 subjects completed the experiment (mean age=23.72, *SD*=4.4). The sample size was chosen based on the assumed effect size of 0.4 from a prior study (Enax, Hu, et al., 2015). For a hierarchical multiple regression analysis, and two levels of the predictor (TL vs. GDA), a sample size of 40 subjects would provide 90% power to detect a significant effect tested at α=0.05. We also conducted two additional experiments with single-nutrient nutrition labels, which are included in the Supplement. All subjects had normal or corrected-to-normal vision. In line with previous studies (Hare et al., 2011; Maier et al., 2015), subjects were tested at varying times during the day but asked to fast four hours prior to the experiment to increase the value of food items (Epstein et al., 2003) and standardize hunger levels. Subjects received €15 endowment for participation as well as their chosen product from a randomly selected choice trial.

2.2 Stimuli

A set of 50 healthy and 50 unhealthy packaged products were obtained from the internet and presented on a black background (resolution: 1920 × 1200 pixel). Nutrition labels were taken from the producer's nutrition information for the product and included sugar, fat, saturated fat, salt, and calories. The labels were presented either numerically with percentages (GDA) or more saliently, using the color-coded TL; see Figure 2 for the stimuli. The GDA percentage values were extracted from the CIAA (CIAA (EU Food and Drink Confederation), 2014) and the TL guidance values from the Food Standards Agency's website (Department of Health & Food Standards Agency (FSA), 2013). Note that calories were not colored, as no guidance values from the FSA exist. GDA and TL labels were of the same size and denoted the respective nutrition value per 100g. We used the classification of healthy versus unhealthy products as described in (Enax, Hu, et al., 2015) based on the TL color classification scheme. Specifically, an item was considered healthy if it contained at least one green and no red coded nutrient, and unhealthy if it contained at least one red and no more than one green coded nutrient. No difference between naturally occurring sugar (e.g., fructose) and added sugar (e.g., sucrose) was made. We used the correct nutrition values of products, therefore, nutrition information could be "mixed", in that a label was not completely green or red, but rather green (healthy) or rather red (unhealthy).

Figure 2: Summary of experimental setup: Subjects rated the taste of 100 food products and then chose between products that were either labeled with a traffic light or with a numeric, information based (GDA, guideline daily amount) label. Note that brand names are shadowed here, but were not masked in the real experiment. After the experiment, one trial was randomly selected, and the subjects received the product they chose in this trial.



The design was presented using z-tree (version 3.4.7; Fischbacher, 2007)

2.3 Behavioral paradigm

In line with previous studies investigating the process of how people make choices between food items based on independently collected taste "liking ratings" on a simple Likert scale (Krajbich et al., 2010; Maier et al., 2015; Philiastides & Ratcliff, 2013), we adopted this design but incorporated nutrition labels as additional modulators of value. Therefore, subjects first rated the taste of each product on a discrete Likert scale from –5 to 5 (–5= *do not like at all*, 5= *like very much*) in increments of 1. The items were presented in the center of the screen without any nutrition information. In the main task, subjects made binary choices between healthy and unhealthy food products on the left and right side of the display, see Figure 2. 350 pairs of healthy and unhealthy products were randomly generated. For each individual, once a product was coupled with a TL (or GDA) label, consecutive presentations of this product also occurred with that label. Product-label combinations were randomized across subjects. Whether the healthy product appeared on the left or right side was randomized. TL and GDA trials were interleaved. Trials were separated by an inter-trial interval of 1000 ms (showing a white fixation cross on a black background). No time limits were imposed on these tasks, but subjects were told to make a response as soon as they formed a decision. Subjects indicated their choice by clicking on a button labeled "left" or "right" below the products corresponding to the screen position with the preferred index finger on a standard computer mouse. Items were removed from the screen as soon as a choice was made.

2.4 Data analysis

Behavioral data were analyzed using R (R Core Team, 2013).

Data cleaning: For each individual, we excluded trials in which the RT was two standard deviations above the individual mean RT, as those trials were likely contaminated by non-attention or distraction and are thus problematic for further analyses. As mean RTs are very sensitive to outliers, we first applied a cutoff of 30 s on the RTs. On average, 17 (SD = 5.4, range: 4–41 trials) out of 350 trials were excluded per subject in this experiment. (The effect of label [model "Label", see below] on healthy choices is also significant when using all choices; Z=2.9, p=0.0037).

Regression analysis: To analyze the overall effect of label (GDA versus TL) on healthy choices, a maximal logistic mixed-effects regression analysis was performed with healthy choice as the dependent variable, label type as an independent variable and subjects as random effects, to account for idiosyncratic variation due to individual differences (Winter, 2013), fit by maximum likelihood (Laplace approximation, model "Label"). We then also controlled for liking by adding rating as a covariate in the model (model "Label + Liking"). Subsequently, we tested for an interaction effect between subjective taste ratings and nutrition labels by adding ratings and the interaction between rating and label to the model (model "Label × Liking"). Further, RT data were analyzed using a maximal linear-mixed model. As RT distributions in these binary choices are highly skewed, we log-transformed the RT data. We used label (TL vs. GDA) as a fixed effect, subject as random effect and log-RT as dependent variable.

Diffusion model fits: Diffusion modeling was performed using fast-dm (fast-dm-30, Heidelberg, Germany) as well as the RWiener package implemented in R (Wabersich, 2014) for analyzing the drift rate as a function of preferences as this analysis is currently not supported in fast-dm. We used the chi-square (χ^2) algorithm for diffusion model fitting. In the DDM analyses, we were specifically interested in the following two research questions (RQ1 and RQ2):

RQ 1: If TL labels increase the drift rate towards healthier options, or alternatively if they induce a starting point bias, and

RQ2: if TL labels increase the weight on health, and decrease the weight on taste attributes in the comparison process, compared to the GDA labels (see ω in the DDM equation below).

For all models, a positive drift indicates accumulation towards the "healthy" boundary, whereas a negative drift indicates that information is generally accumulated towards the "unhealthy" boundary. Similarly, a starting point parameter value greater than 0.5 indicates a starting point bias towards the "healthy" boundary, whereas a value below 0.5 indicates a starting point bias towards the "unhealthy" boundary.

For RQ1, we investigated whether TL labels increase the drift rate towards the healthier option. On a single-subject level, data were modeled across taste ratings. Because we presented TL and GDA trials in a random sequence, subjects could not anticipate which type of label would occur on the next trial, and decision boundaries could not be set beforehand. The model "Drift" included two drift rate parameters (for GDA and TL). We further included label-specific inter-trial variability in drift rates to account for the fact that each decision involves a unique pair of items (Krajbich & Smith, 2015; Philiastides & Ratcliff, 2013). We let non-decision time and starting point vary across both labels and set the parameter accounting for variability in non-decision time and inter-trial variability in relative starting point to zero because this makes the estimation of the remaining parameters more robust, even in presence of inter-trial-variability in our data (Voss et al., 2015). We then compared the two drift rates for GDA and TL using a paired-samples t-test.

Testing for model fit: Model fit was assessed using Monte Carlo simulations, which has, in comparison to graphical inspection, the advantage that it leads to a clear criterion for model fit to each subject (Voss et al., 2015). 1000 parameter sets from a multidimensional normal distribution defined by the covariance matrix of estimated parameter values were drawn using the *mvtnorm* package for R (Genz et al., 2014). Then, for each of the 1000 parameter sets, a data set was simulated using the construct-sample tool of fast-dm and then re-fit with the same settings as used for the empirical data. The parameters from the empirical fit were then compared to these distributions of simulated data fits. Any subjects with parameter fits lying outside of the 95% confidence intervals from the simulated fits were excluded from further analysis (Voss et al., 2015). For completeness, we also present the quantile probability plots across subjects (Figure S1).

Alternative models: As the behavioral effect could also be explained by other diffusion model parameters, suggesting a different mechanism for how labels are processed, we tested three alternative models. The model "Drift + Starting Point" included separate parameter estimates for drift rate and starting point bias for each label. The model "Drift + Non-decision" included separate parameter estimates for drift rate and non-decision time for each label. The model "Drift + Starting Point + Non-decision" included separate estimates for drift rate, starting point, and non-decision time for each label. All alternative models accounted for drift rate variability. Variability in non-decision time and inter-trial variability in relative starting point were again set to zero. We then tested for significant differences between TL and GDA using a paired-samples t-test.

Drift as a function of taste ratings: For RQ2, we allowed the drift rate to vary as a function of the taste ratings on a single-subject level. We assumed that

$$RDV_{(t)} = RDV_{(t-1)} + \text{health}_S + (\omega \times (\text{taste}_H - \text{taste}_U)) + \varepsilon$$

where RDV is the relative decision value at time t, health_S is the sensitivity to health (intercept), and ω is the weight on the difference between the taste ratings of the healthy (H) and unhealthy (U) food item. ω multiplies the taste value difference between the healthy and unhealthy option and determines the relative importance of taste in the mean drift rate. The model assumes that it takes time to accumulate and compare evidence for the options until a pre-specified level of confidence is reached. The rate of evidence accumulation depends linearly on the difference between the underlying subjective taste values. For estimation purposes (because we did not have enough data in each bin to properly fit the model), we further binned the taste ratings into three coarse bins: unhealthy preferred [rating difference from –10 to –4], roughly equally liked [–3 to 3] and healthy preferred [4 to 10]. We also included Gaussian noise (ε). See the Supplement for further logit analyses investigating whether the labels change the absolute or the relative weight of taste and health attributes, as well as rating-specific drift rates, which were calculated using a jackknifing procedure.

3 Results

3.1 Choice and reaction time data analyses

We found a significant effect of label on healthy choice (model "Label", estimate (standard error, SE): 0.25 (0.08); Z=2.82, p<0.01, intercept: –0.09), with higher proportions of healthy choices in the TL compared to the GDA condition. The effect of label was still significant, and even larger (0.33), when statistically controlling for liking (model "Label + Liking"). As expected we found that liking ratings significantly affected choices (main effect label: estimate (SE): 0.33 (0.10); Z=3.43, p<0.001; main effect liking: estimate (SE): 0.55 (0.03); Z=17.15, p<0.001, intercept: 0.17).

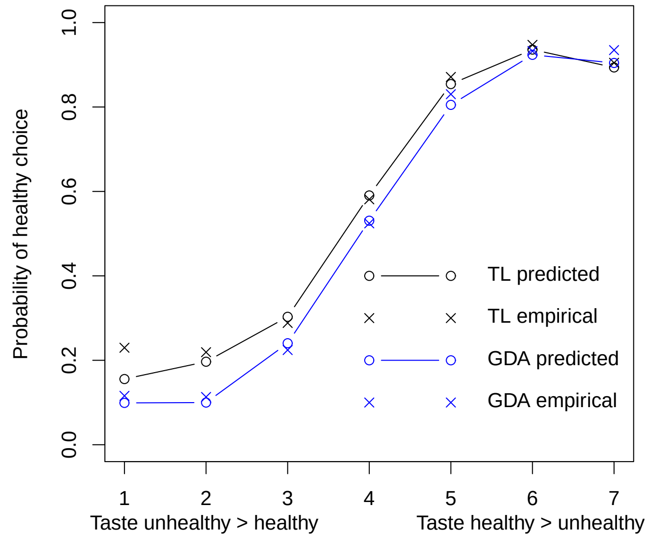
Further, we found an almost significant interaction between ratings and label (model "Label × Liking", interaction effect: estimate (SE): –0.05 (0.02) Z=1.75, p=0.08; main effect label: estimate (SE): 0.30 (0.10); Z=3.12, p=0.002; main effect liking: estimate (SE): 0.58 (0.03); Z=16.7, p<0.001; intercept: 0.18); see Figure 3. Note that the almost significant interaction term probably does not reflect a true psychological difference in the effect of the TL labels when taste healthy > unhealthy, but is rather the product of a ceiling effect where the healthy item is almost always being chosen, and so there is little room for the TL labels to have an additional effect. In other words, this is likely a removable interaction (Loftus 1978; Wagenmakers et al. 2012).

We also analyzed whether there was a difference in RT depending on the label using a mixed-effects linear regression analysis using log-transformed RT data. We found a trending effect of label on RTs in that subjects were somewhat faster in the GDA condition (t=1.43, p=0.16; mean log-RT for GDA=0.766, SD=0.55; mean log-RT for TL=0.78, SD=0.53)

3.2 Diffusion model analyses

For RQ1, we investigated whether drift rates differ between the two labels at a single-subject level (model "Drift"). The drift rate towards the healthy option is significantly higher for the TL label, compared to the numeric GDA

Figure 3: Empirical probability of healthy choice and predicted probabilities as a function of taste. Note that for display purposes only, ratings were binned into seven larger bins (from –10 to –8, –7 to –5, –4 to –2, –1 to 1, 2 to 4, 5 to 7 and 8 to 10). Values and confidence intervals for healthy choices per rating bin were predicted from a logistic mixed regression model (model "Label × Liking" with binned liking ratings).



label (t(43)=2.3, p=0.029; drift rate mean GDA=-0.10, TL=0.05)). Monte-Carlo simulations as well as quantile-probability plots were used to assess model fit. Since fast-dm minimizes the χ^2 value, high χ^2 values are indicative of a poor fit. We used the 95% quantile of the χ^2 distribution and determined whether our values were below this criterion. All of our fits were below the obtained critical value, indicating an acceptable model fit in all cases; therefore, no subjects were excluded. See also the quantile probability plot across subjects (Figure S1 in the Supplement).

We then tested alternative models to investigate whether other diffusion model parameters can capture the observed behavioral effect, which would suggest a different underlying psychological process. We only find significant differences between drift rates but not in non-decision time or starting point bias for TL and GDA; see Table 1 and Figure 4.

For RQ2, we let the drift rate vary as a function of the relative desirability of the taste of the products, that is, the difference between the taste of the healthy product and the taste of the unhealthy product. As expected, the salient TL labels increase the sensitivity (s) to health attributes (mean health_S GDA=0.002, SEM=0.012; mean health_S TL=0.093, SEM=0.013, t(43)=2.60, p=0.013). Also, salient labels reduce the weight (ω) subjects place on taste attributes (mean ω GDA=0.77, SEM=0.01; mean ω TL=0.71, SEM=0.012; t(43)=2.331, p=0.021); see Figure 5 and also the additional

Table 1: Alternative diffusion models.

		Mean		SEM[a]				
Model	Parameters	GDA	TL	GDA	TL	t-value	p-value	Mean model $\chi^{2\ b}$
1.	Drift rate	–0.12	0.07	0.02	0.02	**2.34**	**0.02**	18.54
	Starting Point	0.50	0.49	0.01	0.01	0.74	0.46	
2.	Drift rate	–0.09	0.05	0.02	0.02	**2.13**	**0.04**	18.89
	Non-decision time	0.76	0.76	0.01	0.01	0.54	0.60	
3.	Drift rate	–0.11	0.05	0.02	0.02	**2.16**	**0.04**	17.19
	Starting Point	0.50	0.50	0.01	0.01	0.36	0.72	
	Non-decision time	0.77	0.77	0.01	0.01	0.29	0.77	

[a] Standard error of the mean.

[b] Does not account for model complexity.

Figure 4: Results from Model "Drift + Starting Point + Non-decision": Only drift rates differ significantly for TL versus GDA. * indicates $p<0.05$.

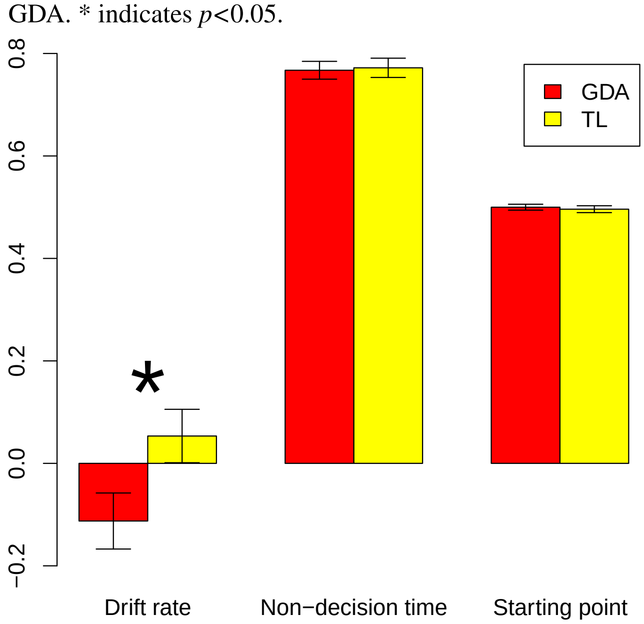
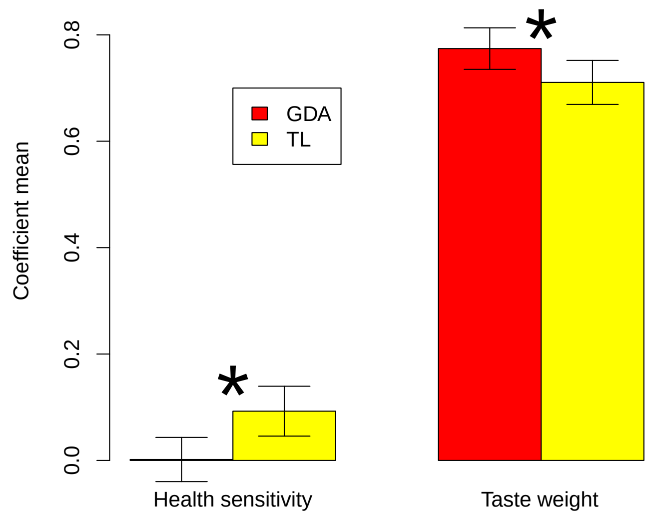


Figure 5: Relative decision value as a function of the weight on taste and the sensitivity to health. We find that TL labels increase the sensitivity to health attributes, and decrease the weight subjects put on taste attributes. Abbreviations: $health_S$, sensitivity to health (intercept); ω = weight on taste; GDA=guideline daily amount; TL= traffic light. * $p<0.05$.



analyses in the Supplement, where we further investigated whether the labels change the relative or absolute weight on health and taste attributes. Rating-specific drift rates were analyzed using a jackknifing procedure (see Supplement).

4 Discussion

In this study, we investigated the cognitive mechanism underlying value-based decisions with nutrition labels as modulators of value. As expected, the percentage of healthy choices increased when the product was labeled with a color-coded, compared to a purely numeric label. We further used drift diffusion modeling to draw conclusions about the underlying cognitive mechanism, which has not been addressed in previous studies. We found that the drift rate towards the healthier option is increased in case of color-coded labeling, compared to the purely numerical counterpart, suggesting that health information and taste preferences are integrated in the decision process. In contrast, we do not find evidence for a simple stimulus-response bias due to color-coded labels irrespective of the items' features. Last, our data suggests that subjects put less weight on taste attributes, and more weight on health attributes when choosing between color-coded labeled products.

Manipulating the amount of attention paid to health features, for example via overt instruction (Hare et al., 2011) or salient cigarette warnings (Borland et al., 2009), can increase the weight placed on health features, and thereby alter the choice process (Fehr & Rangel, 2011). Our traditional regression analyses revealed a higher probability to choose the healthy product when presented with more salient, color-coded labels. This is in line with previous studies that showed that color-coded labels increase the identification and choice of healthier options (Borgmeier & Westenhoefer, 2009; Hawley et al., 2013; Hersey et al., 2013; Kelly et al., 2009; Roberto et al., 2012; van Herpen & Trijp, 2011). Schulte-Mecklenbeck and colleagues (2013) analyzed strategy use in information acquisition during food choices and found that choices are often based on very simple heuristics, which reduce computation time. As GDA labels are cognitively more demanding than TL labels, they likely provide information that is harder to process, which is in turn utilized less. In this study, we did not classify subject's overt behavior into choice strategies. Therefore, future studies using strategy analysis in combination with actual process tracing data (e.g., eye-tracking or mouse-tracking) would be valuable to analyze, for example, if salient labels interfere with an automatic preference-based choice heuristic or actually promote a fully-informed choice strategy.

To our knowledge, this is the first study to also analyze how exactly health information is integrated into the decision-making process, and how this is changed by the more salient TL display, using empirical choice and RT data in a DDM. This type of decision is interesting because subjects need to combine information from pictorial stimuli (food products) as well as symbolic and numeric information (labels). Although DDMs have been used before in consumer contexts, it was not known *a priori* whether the DDM could account for the impact of nutrition information on the valuation process. Importantly, the DDM provides information above and beyond traditional logit analyses, as it estimates different parameters accounting for various decisional processes, informing us not only whether health information influences choices but also how exactly health information is incorporated into the decision. In particular, we investigated whether the salient health information influences the valuation process, or whether it induces a simple response bias. Our data support the hypothesis that salient, color-coded nutrition information directly influences the valuation process in favor of healthier options, as the behavioral effect of nutrition labels could only be explained by changes in drift rate, but not in starting point bias. This finding provides evidence that nutrition label information and taste preferences are incorporated into the valuation process, ruling out the alternative mechanism that these labels only induce an automatic stimulus-response choice bias. Further, we find that for saliently labeled products the weight on taste gets discounted, while the sensitivity to health increases.

In two additional experiments, subjects made the same binary choices, but products were labeled with simplified nutrition information, displaying only the amount of one nutrient, that is, sugar. Overall, subjects made less healthy choices when confronted with information on only one nutrient (sugar). The effects of simplified nutrition information were weaker, suggesting that more comprehensive, salient information is more effective (see Supplement and Table S1).

It is possible, given that we used the actual nutritional information for each product, that healthiness could be correlated with other features of the products. Thus the changes in behavior due to the TL vs. GDA labels cannot unambiguously be attributed to an increase in the weight on health information, though we do see this as the most likely explanation. Importantly, our use of real products paired with real nutritional information implies that, in any case, the use of TL labels in real-world applications should promote choosing healthy products.

As many food decisions occur automatically or habitually (Rangel, 2013; Wansink & Sobal, 2007), nutrition labels may have a decisive role in triggering goal-directed decisions that incorporate not only taste considerations, but also long-term health outcomes. We demonstrate that salient labels increase the integration of health considerations into the decision process; salient nutrition labels may therefore interfere with automatic decision processes and trigger reevaluation of the choice options. The results have obvious implications for public policy interventions. Environmental nudges, including understandable nutrition labels, are important pillars of public policy interventions aiming at improving dietary preferences and choices (Hawkes et al., 2015). Salient TL nutrition labels seem to be a feasible option to increase the consideration of health attributes in every-day choice situations to encourage consumers to purchase the healthier product. Of course, the unnatural size and placement of nutrition labels may have influenced the valuation process. Previous studies have shown that display size is an important determinant of attention (Bialkova & van Trijp, 2010), therefore, future studies with a more natural design are necessary. In addition, real-world choice alternatives include many other product attributes, next to nutrition labeling, as well as subjects' individual characteristics, which were shown to influence nutrition label use and understanding (Miller & Cassady, 2012). The impact of these factors and their interaction with nutrition labels warrants further investigation.

In sum, the results presented in this study provide insights into the nature of computational processes that take place during simple choices between two food products along with health attribute labels. Our results suggest that health information can be successfully coalesced with taste-preferences based on representational values during the decision-making process.

References

Annett, L. E., Muralidharan, V., Boxall, P. c., Cash, S. b., & Wismer, W. v. (2008). Influence of Health and Environmental Information on Hedonic Evaluation of Organic and Conventional Bread. *Journal of Food Science*, *73*(4), H50–H57. http://doi.org/10.1111/j.1750-3841.2008.00723.x.

Becker, M. W., Bello, N. M., Sundar, R. P., Peltier, C., & Bix, L. (2015). Front of pack labels enhance attention to nutrition information in novel and commercial brands. *Food Policy*, *56*, 76–86. http://doi.org/10.1016/j.foodpol.2015.08.001.

Bialkova, S., Grunert, K. G., Juhl, H. J., Wasowicz-Kirylo, G., Stysko-Kunkowska, M., & van Trijp, H. C. M. (2014). Attention mediates the effect of nutrition label information on consumers' choice. Evidence from a choice experiment involving eye-tracking. *Appetite*, *76*, 66–75. http://doi.org/10.1016/j.appet.2013.11.021.

Bialkova, S., & van Trijp, H. (2010). What determines consumer attention to nutrition labels? *Food Quality and Preference*, *21*(8), 1042–1051. http://doi.org/10.1016/j.foodqual.2010.07.001.

Bogacz, R. (2007). Optimal decision-making theories: linking neurobiology with behaviour. *Trends in Cognitive Sciences*, *11*(3), 118–125. http://doi.org/10.1016/j.tics.2006.12.006.

Borgmeier, I., & Westenhoefer, J. (2009). Impact of different food label formats on healthiness evaluation and food choice of consumers: a randomized-controlled study. *BMC Public Health*, *9*(1), 184. http://doi.org/10.1186/1471-2458-9-184.

Borland, R., Wilson, N., Fong, G. T., Hammond, D., Cummings, K. M., Yong, H.-H., … McNeill, A. (2009). Impact of graphic and text warnings on cigarette packs: findings from four countries over five years. *Tobacco Control*, *18*(5), 358–364. http://doi.org/10.1136/tc.2008.028043.

Bruce, A. S., Bruce, J. M., Black, W. R., Lepping, R. J., Henry, J. M., Cherry, J. B. C., … Savage, C. R. (2014). Branding and a child's brain: an fMRI study of neural responses to logos. *Social Cognitive and Affective Neuroscience*, *9*(1), 118–122. http://doi.org/10.1093/scan/nss109.

Busemeyer, J. R., & Townsend, J. T. (1993). Decision field theory: A dynamic-cognitive approach to decision making in an uncertain environment. *Psychological Review*, *100*(3), 432–459. http://doi.org/10.1037/0033-295X.100.3.432.

Campos, S., Doxey, J., & Hammond, D. (2011). Nutrition labels on pre-packaged foods: a systematic review. *Public Health Nutrition*, *14*(8), 1496–1506. http://doi.org/10.1017/S1368980010003290.

CIAA (EU Food and Drink Confederation). (2014, September 19). Guideline Daily Amounts (GDAs) - GDAs Explained. Retrieved September 19, 2014, from http://gda.fooddrinkeurope.eu/asp2/what_are_gdas.asp.

Cowburn, G., & Stockley, L. (2005). Consumer understanding and use of nutrition labelling: a systematic review. *Public Health Nutrition*, *8*(1), 21–28.

De Martino, B., Fleming, S. M., Garrett, N., & Dolan, R. J. (2013). Confidence in value-based choice. *Nature Neuroscience*, *16*(1), 105–110. http://doi.org/10.1038/nn.3279.

Department of Health & Food Standards Agency (FSA). (2013, June 19). Guide to creating a front of Pack (FoP) Nutrition Label for Pre-packed Products sold through Retail Outlets. Retrieved September 19, 2014, from https://www.gov.uk/government/publications/front-of-pack-nutrition-labelling-guidance.

Enax, L., Hu, Y., Trautner, P., & Weber, B. (2015). Nutrition labels influence value computation of food products in the ventromedial prefrontal cortex. *Obesity*, *23*(4), 786–792. http://doi.org/10.1002/oby.21027.

Enax, L., Krapp, V., Piehl, A., & Weber, B. (2015). Effects of social sustainability signaling on neural valuation signals and taste-experience of food products. *Frontiers in Behavioral Neuroscience*, 247. http://doi.org/10.3389/fnbeh.2015.00247.

Enax, L., Weber, B., Ahlers, M., Kaiser, U., Diethelm, K., Holtkamp, D., … Kersting, M. (2015). Food packaging cues influence taste perception and increase effort provision for a recommended snack product in children. *Frontiers in Psychology*, *6*, 882. http://doi.org/10.3389/fpsyg.2015.00882.

Epstein, L. H., Truesdale, R., Wojcik, A., Paluch, R. A., & Raynor, H. A. (2003). Effects of deprivation on hedonics and reinforcing value of food. *Physiology & Behavior*, *78*(2), 221–227.

Fehr, E., & Rangel, A. (2011). Neuroeconomic Foundations of Economic Choice — Recent Advances. *Journal of Economic Perspectives*, *25*(4), 3–30. http://doi.org/10.1257/jep.25.4.3.

Fernqvist, F., & Ekelund, L. (2013). Consumer attitudes towards origin and organic — the role of credence labels on consumers' liking of tomatoes. *European Journal of Horticultural Science. 78*(4), 184–190.

Fischbacher, U. (2007). z-Tree: Zurich toolbox for ready-made economic experiments. *Experimental Economics*, *10*(2), 171–178. http://doi.org/10.1007/s10683-006-9159-4.

Genz, A., Bretz, F., Miwa, T., Mi, X., Leisch, F., Scheipl, F., … Hothorn, T. (2014). mvtnorm: Multivariate normal and t distributions (Version 1.0–2). Retrieved from http://cran.r-project.org/web/packages/mvtnorm/index.html.

Gorton, D., Ni Mhurchu, C., Chen, M.-H., & Dixon, R. (2009). Nutrition labels: a survey of use, understanding and preferences among ethnically diverse shoppers in New Zealand. *Public Health Nutrition*, *12*(9), 1359–1365. http://doi.org/10.1017/S1368980008004059.

Graham, D. J., & Jeffery, R. W. (2012). Predictors of nutrition label viewing during food purchase decision making: an eye tracking investigation. *Public Health Nutrition*, *15*(2), 189–197. http://doi.org/10.1017/S1368980011001303.

Graham, D. J., Orquin, J. L., & Visschers, V. H. M. (2012). Eye tracking and nutrition label use: A review of the literature and recommendations for label enhancement. *Food Policy*, *37*(4), 378–382. http://doi.org/10.1016/j.foodpol.2012.03.004.

Grunert, K. G., Fernández-Celemín, L., Wills, J. M., Storcksdieck genannt Bonsmann, S., & Nureeva, L. (2010). Use and understanding of nutrition information on food labels in six European countries. *Journal of Public Health*, *18*(3), 261–277. http://doi.org/10.1007/s10389-009-0307-0.

Grunert, K. G., & Wills, J. M. (2007). A review of European research on consumer response to nutrition information on food labels. *Journal of Public Health*, *15*(5), 385–399. http://doi.org/10.1007/s10389-007-0101-9.

Hamlin, R. P., McNeill, L. S., & Moore, V. (2015). The impact of front-of-pack nutrition labels on consumer product evaluation and choice: an experimental study. *Public Health Nutrition*, *18*(12), 2126–2134. http://doi.org/10.1017/S1368980014002997.

Hare, T. A., Malmaud, J., & Rangel, A. (2011). Focusing attention on the health aspects of foods changes value signals in vmPFC and improves dietary choice. *The Journal of Neuroscience: The Official Journal of the Society for Neuroscience*, *31*(30), 11077–11087. http://doi.org/10.1523/JNEUROSCI.6383-10.2011.

Hawkes, C., Smith, T. G., Jewell, J., Wardle, J., Hammond, R. A., Friel, S., … Kain, J. (2015). Smart food policies for obesity prevention. *The Lancet*, *385*(9985), 2410–2421. http://doi.org/10.1016/S0140-6736(14)61745-1.

Hawley, K. L., Roberto, C. A., Bragg, M. A., Liu, P. J., Schwartz, M. B., & Brownell, K. D. (2013). The science on front-of-package food labels. *Public Health Nutrition*, *16*(3), 430–439. http://doi.org/10.1017/S1368980012000754.

Helfer, P., & Shultz, T. R. (2014). The effects of nutrition labeling on consumer food choice: a psychological experiment and computational model. *Annals of the New York Academy of Sciences*, *1331*, 174–185. http://doi.org/10.1111/nyas.12461.

Hersey, J. C., Wohlgenant, K. C., Arsenault, J. E., Kosa, K. M., & Muth, M. K. (2013). Effects of front-of-package and shelf nutrition labeling systems on consumers. *Nutrition Reviews*, *71*(1), 1–14. http://doi.org/10.1111/nure.12000.

Hübl, G., & Trifts, V. (2000). Consumer Decision Making in Online Shopping Environments: The Effects of Interactive Decision Aids. *Marketing Science*, *19*(1), 4–21. http://doi.org/10.1287/mksc.19.1.4.15178.

Jones, G., & Richardson, M. (2007). An objective examination of consumer perception of nutrition information based on healthiness ratings and eye movements. *Public Health Nutrition*, *10*(3), 238–244. http://doi.org/10.1017/S1368980007258513.

Kelly, B., Hughes, C., Chapman, K., Louie, J. C.-Y., Dixon, H., Crawford, J., … Slevin, T. (2009). Consumer testing of the acceptability and effectiveness of front-of-pack food labelling systems for the Australian grocery market. *Health Promotion International*, *24*(2), 120–129. http://doi.org/10.1093/heapro/dap012.

Krajbich, I., Armel, C., & Rangel, A. (2010). Visual fixations and the computation and comparison of value in simple choice. *Nature Neuroscience*, *13*(10), 1292–1298. http://doi.org/10.1038/nn.2635.

Krajbich, I., Oud, B., & Fehr, E. (2014). Benefits of neuroeconomic modeling: new policy interventions and predictors of preference. *American Economic Review*, *104*(5), 501–506. http://doi.org/10.1257/aer.104.5.501.

Krajbich, I., & Smith, S. M. (2015). Modeling Eye Movements and Response Times in Consumer Choice. *Journal of Agricultural & Food Industrial Organization*, *13*(1), 55–72. http://doi.org/10.1515/jafio-2015-0016.

Levy, D. E., Riis, J., Sonnenberg, L. M., Barraclough, S. J., & Thorndike, A. N. (2012). Food choices of minority and low-income employees: a cafeteria intervention. *American Journal of Preventive Medicine*, *43*(3), 240–248. http://doi.org/10.1016/j.amepre.2012.05.004.

Loftus, G. R. (1978). On interpretation of interactions. *Memory & Cognition*, *6*(3), 312–319. http://doi.org/10.3758/BF03197461.

Maier, S. U., Makwana, A. B., & Hare, T. A. (2015). Acute stress impairs self-control in goal-directed choice by altering multiple functional connections within the brain's decision circuits. *Neuron*, *87*(3), 621–631. http://doi.org/10.1016/j.neuron.2015.07.005.

Maubach, N., & Hoek, J. (2008). The effect of alternative nutrition information formats on consumers' evaluations of a children's breakfast cereal. *Partnerships, Proof and Practice - International Nonprofit and Social Marketing Conference 2008 - Proceedings*. Retrieved from http://ro.uow.edu.au/insm08/1.

Miller, L. M., & Cassady, D. L. (2012). Making Healthy Food Choices Using Nutrition Facts Panels: The Roles of Knowledge, Motivation, Dietary Modifications Goals, and Age. *Appetite*, *59*(1), 129–139. http://doi.org/10.1016/j.appet.2012.04.009.

Moser, R., Raffaelli, R., & Thilmany, D. D. (2011). Consumer Preferences for Fruit and Vegetables with Credence-Based Attributes: A Review. *International Food and Agribusiness Management Review*, *14*(2). Retrieved from https://ideas.repec.org/a/ags/ifaamr/103990.html.

Ng, J., Stice, E., Yokum, S., & Bohon, C. (2011). An fMRI study of obesity, food reward, and perceived caloric density. Does a low-fat label make food less appealing? *Appetite*, *57*(1), 65–72. http://doi.org/10.1016/j.appet.2011.03.017.

Orquin, J. L., Scholderer, J., & Jeppesen, H. (2012). What you see is what you buy: How saliency and surface size of packaging elements affect attention and choice. *Society for Advancement of Behavioural Economics*. Retrieved from http://scholar.google.com/scholar?cluster=11288207893494723098&hl=en&oi=scholarr.

Philiastides, M. G., & Ratcliff, R. (2013). Influence of branding on preference-based decision making. *Psychological Science*, *24*(7), 1208–1215. http://doi.org/10.1177/0956797612470701.

R Core Team. (2013). *R: A language and environment for statistical computing.* (Vol. R Foundation for Statistical Computing). Vienna, Austria. Retrieved from http://www.R-project.org/..

Raghunathan, R., Naylor, R. W., & Hoyer, W. D. (2006). The unhealthy = tasty intuition and its effects on taste inferences, enjoyment, and choice of food products. *Journal of Marketing*, *70*(4), 170–184. http://dx.doi.org/10.1509/jmkg.70.4.170.

Rangel, A. (2013). Regulation of dietary choice by the decision-making circuitry. *Nature Neuroscience*, *16*(12), 1717–1724. http://doi.org/10.1038/nn.3561.

Ratcliff, R. (1978). A theory of memory retrieval. *Psychological Review*, *85*(2), 59–108. http://doi.org/10.1037/0033-295X.85.2.59.

Ratcliff, R., & Smith, P. L. (2004). A comparison of sequential sampling models for two-choice reaction time. *Psychological Review*, *111*(2), 333–367. http://doi.org/10.1037/0033-295X.111.2.333.

Roberto, C. A., Bragg, M. A., Schwartz, M. B., Seamans, M. J., Musicus, A., Novak, N., & Brownell, K. D. (2012). Facts up front versus traffic light food labels: a randomized controlled trial. *American Journal of Preventive Medicine*, *43*(2), 134–141. http://doi.org/10.1016/j.amepre.2012.04.022.

Sabbe, S., Verbeke, W., Deliza, R., Matta, V., & Van Damme, P. (2009). Effect of a health claim and personal characteristics on consumer acceptance of fruit juices with different concentrations of açaí (Euterpe oleracea Mart.). *Appetite*, *53*(1), 84–92. http://doi.org/10.1016/j.appet.2009.05.014.

Savoie, N., Barlow Gale, K., Harvey, K. L., Binnie, M. A., & Pasut, L. (2013). Consumer perceptions of front-of-package labelling systems and healthiness of foods. *Canadian Journal of Public Health = Revue Canadienne De Santé Publique*, *104*(5), e359-363.

Sonnenberg, L., Gelsomin, E., Levy, D. E., Riis, J., Barraclough, S., & Thorndike, A. N. (2013). A traffic light food labeling intervention increases consumer awareness of health and healthy choices at the point-of-purchase. *Preventive Medicine*, *57*(4), 253–257. http://doi.org/10.1016/j.ypmed.2013.07.001.

Taubinsky, D., Morris, C. L., Schuldt, J. P., Chabris, C. F., & Laibson, D. I. (2009). The allocation of time in decision-making. (Scholarly Articles No. 4481495). Harvard University Department of Economics. Retrieved from https://ideas.repec.org/p/hrv/faseco/4481495.html.

Temple, N. J., & Fraser, J. (2014). Food labels: a critical assessment. *Nutrition*, *30*(3), 257–260. http://doi.org/10.1016/j.nut.2013.06.012.

Thaler, H., & Sunstein, C. R. (2008). Nudge: Improving decisions about health, wealth, and happiness. *Constitutional Political Economy*, *19*(4), 356–360. http://doi.org/10.1007/s10602-008-9056-2.

Thorndike, A. N., Sonnenberg, L., Riis, J., Barraclough, S., & Levy, D. E. (2012). A 2-phase labeling and choice architecture intervention to improve healthy food and beverage choices. *American Journal of Public Health*, *102*(3), 527–533. http://doi.org/10.2105/AJPH.2011.300391.

Trudel, R., & Murray, K. B. (2011). Why didn't I think of that? Self-regulation through selective information processing. *Journal of Marketing Research*, *48*(4), 701–712. http://doi.org/10.1509/jmkr.48.4.701.

Trudel, R., Murray, K. B., Kim, S., & Chen, S. (2015). The impact of traffic light color-coding on food health perceptions and choice. *Journal of Experimental Psychology: Applied*, *21*(3), 255–275. http://doi.org/10.1037/xap0000049.

van Herpen, E., & Trijp, H. C. M. van. (2011). Front-of-pack nutrition labels. Their effect on attention and choices when consumers have varying goals and time constraints. *Appetite*, *57*(1), 148–160. http://doi.org/10.1016/j.appet.2011.04.011.

Voss, A., Nagler, M., & Lerche, V. (2013). Diffusion models in experimental psychology: A practical introduction. *Experimental Psychology*, *60*(6), 385–402. http://doi.org/10.1027/1618-3169/a000218.

Voss, A., Voss, J., & Lerche, V. (2015). Assessing cognitive processes with diffusion model analyses: a tutorial based on fast-dm-30. *Frontiers in Psychology*, *6*, 336. http://doi.org/10.3389/fpsyg.2015.00336.

Wabersich, D. (2014). RWiener: Wiener process distribution functions (Version 1.2-0). Retrieved from http://cran.r-project.org/web/packages/RWiener/index.html.

Wagenmakers, E.-J., Krypotos, A.-M., Criss, A. H., & Iverson, G. (2012). On the interpretation of removable interactions: A survey of the field 33 years after Loftus. *Memory & Cognition*, *40*(2), 145–160. http://doi.org/10.3758/s13421-011-0158-0.

Wansink, B., & Chandon, P. (2006). Can “low-fat” nutrition labels lead to obesity? *Journal of Marketing Research*, *43*(4), 605–617. http://doi.org/10.1509/jmkr.43.4.605.

Wansink, B., & Sobal, J. (2007). Mindless eating the 200 daily food decisions we overlook. *Environment and Behavior*, *39*(1), 106–123. http://doi.org/10.1177/0013916506295573.

Winter, B. (2013). Linear models and linear mixed effects models in R with linguistic applications. Retrieved March 16, 2015, from http://arxiv.org/pdf/1308.5499.pdf.