

The Hungry Lens: Hunger Shifts Attention and Attribute Weighting in Dietary Choice

Reviewed Preprint

v1 • December 19, 2024

Not revised

Jennifer March , Sebastian Gluth

Department of Psychology and Hamburg Center of Neuroscience, Universität Hamburg, Hamburg, Germany

 https://en.wikipedia.org/wiki/Open_access Copyright information

eLife Assessment

This is an **important** study showing that people who are hungry (vs. sated) put more weight on taste (vs. health) in their food choices. The experiment is well-designed and includes choice behavior, eye-tracking, and state-of-the-art computational modeling, resulting in **compelling** evidence supporting the conclusions. The manuscript could be further improved through appropriate revisions to data analysis and interpretation.

<https://doi.org/10.7554/eLife.103736.1.sa4>

Abstract

Hunger is a biological drive which can promote unhealthy dietary decisions. Yet, the cognitive mechanisms underlying this effect, and in particular the interactive role of attention and choice processes, remain elusive. To address this gap, we conducted an eye-tracking experiment, in which 70 participants completed a multi-attribute food choice task in hungry and sated states. Confirming our preregistered hypotheses, participants' preference for tasty over healthy food items was amplified by hunger. Attention mediated this influence of hunger, as hungry participants focused more on tasty options, leading them to make less healthy decisions. Rigorous model comparisons revealed that an extension of the recently proposed multi-attribute attentional drift diffusion model best explained choice and response times. According to this model, hunger did not only increase the relative taste compared to health weight of, but it also increased the fixation-related discounting of health but not taste information. Our results suggest that the cognitive mechanisms underlying unhealthy dietary decisions under hunger are characterized by a nuanced interplay between attention and the significance assigned to the options' underlying attributes.

Introduction

Throughout a single day we make numerous food choices. These choices are largely influenced by the food and its environment as well as by the decision maker's trait and state factors (Chen & Antonelli, 2020 ). For example, it has been shown that health information such as nutritional

scores on food options (Ramanani et al., 2020) or health primes (Hare et al., 2011; Sullivan & Huettel, 2021) can increase the number of healthy choices. On the other hand, a hungry decision maker is more likely to make unhealthy decisions (Cheung et al., 2017; Hoefling & Strack 2010). Evolutionary, a preference for energy dense foods was adaptive and ensured survival under conditions of scarcity (Hanßen et al., 2022; Mattson, 2019). While, the food environment in Western societies has become increasingly obesogenic, with high caloric food options being affordable and easily available, the neurobiological mechanism continues to reward the consumption of energy dense foods contributing to a global surge in obesity rates (World Obesity Federation 2023, World Health Organization, 2021). The critical involvement of reward circuitries in the brain in determining food choice highlights the importance of cognitive affective drivers, alongside homeostatic ones, in shaping food-related behavior (Plassmann et al., 2021; Rangel, 2013). Here, we set out to shed light on these cognitive mechanisms underlying food choice which drive energy intake and weight, by investigating the effect of hunger on attention and valuation processes in multi-attribute dietary choice.

Consistent with the evolutionary mechanism that reinforces high-energy dense food options, behavioral (Cameron et al., 2014; Cheung et al., 2017; Epstein et al., 2003) and neuroimaging studies (e.g., Banica et al., 2023; Dagher, 2012; Malik et al., 2008) indicate that under hunger (high-caloric) food options are viewed more rewarding, are more frequently chosen over healthy alternatives, and draw more attention. Meta-analyses have revealed an attentional bias towards food versus neutral stimuli, which was further amplified by hunger state (Pool et al. 2012; Hardman et al 2021). Given these findings, it appears critical to thoroughly understand the interplay between attention and decision-making processes in shaping maladaptive food choice under hunger. To better explain the mechanisms by which hunger affects attention and valuation processes in dietary choice, we leverage recent advances in modeling attentional dynamics in the accumulation of evidence in decisionmaking (Gluth et al., 2020; Krajbich et al., 2010; Shimojo et al., 2003). This work has provided evidence for a strong positive association between the time people spend looking at a (food) option and the probability with which they choose it (Krajbich, 2019). Recently, these models have also incorporated the distinct attentional influence of the options' underlying attributes such as taste and health (Fisher, 2021; Yang & Krajbich, 2023). To the best of our knowledge, there is no study modeling attention and choice dynamics under different hunger states leaving the cognitive and attentional mechanisms underlying hunger-driven food choice unknown.

To fill this gap, we conducted a within-subject experiment, in which 70 participants completed a binary food choice task in hungry and sated states while their eye-movements were being recorded (**Figure 1**). The considered attributes of the binary options were taste and health as represented by food images and their nutritional scores, respectively. Confirming our preregistered hypotheses, participants were more likely to choose tasty over healthy food items, and this difference was amplified under hunger. Notably, attention mediated the influence of hunger on dietary decisions, as participants focused more on taste information under hunger, leading them to make less healthy decisions. To better understand the cognitive mechanisms underlying hunger-driven dietary choice, we implemented different variants of the Diffusion Decision Model (DDM, Ratcliff, 1978), which included the consideration of both attributes (Maier et al., 2020; Sullivan & Huettel, 2021) and the incorporation and extension of attentional mechanisms (Fisher, 2021; Krajbich et al., 2010; Yang & Krajbich, 2023). Critically, we extended the recently proposed multi-attribute attentional DDM (Yang & Krajbich, 2023) to allow the discounting of unattended information to differ across different attributes (here: taste vs. health). This model did not only provide the best account of our behavioral data, but also revealed a two-fold mechanism, wherein hunger affects valuation of choice options by shifting the relative weighting of taste information and by exacerbating the attentional discounting of health (but not taste) information.

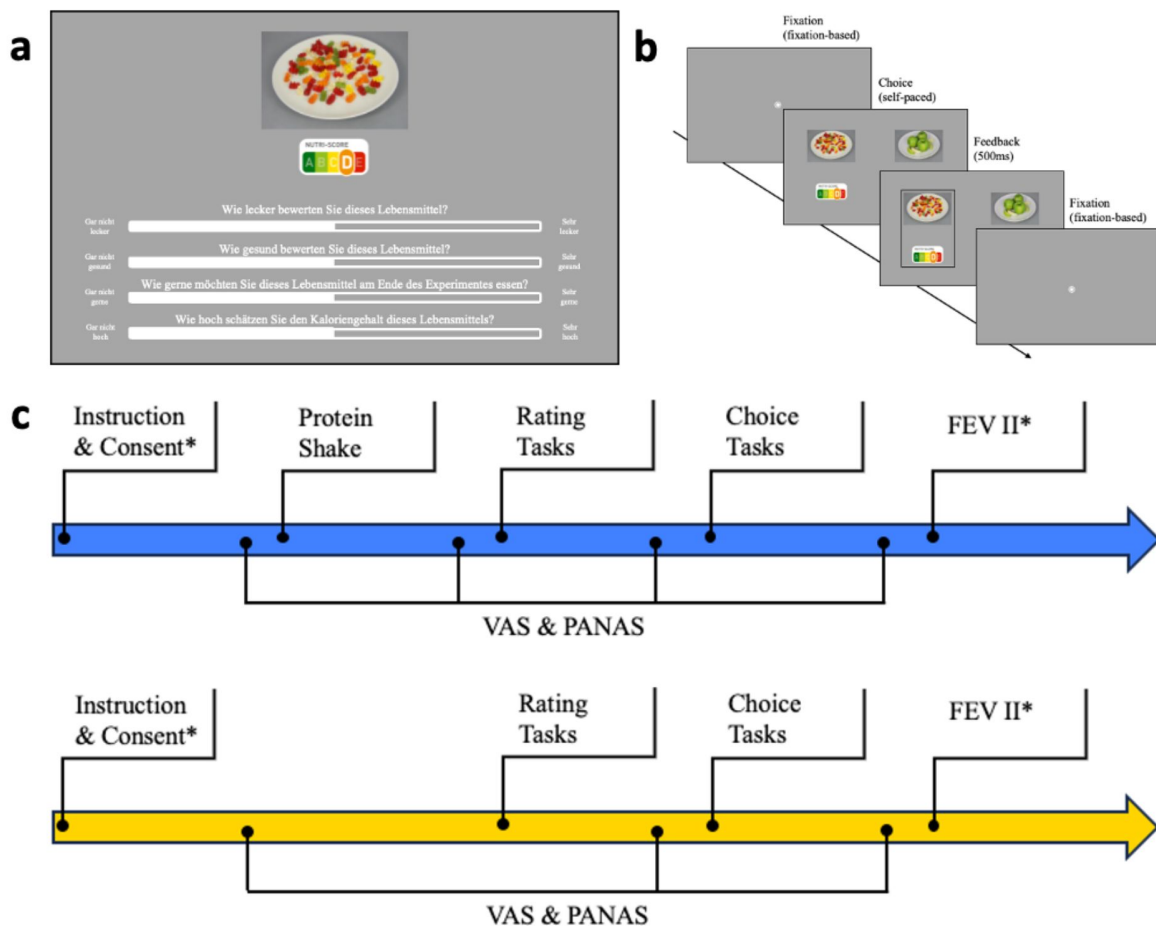


Figure 1

Experimental Design

a) Food rating task. Participants rated all food images and their corresponding Nutri-Scores in terms of taste, health, wanting and perceived caloric content on a continuous scale **b)** Trial sequence of food choice task. In each trial, participants made a binary choice between two food options represented by food image and corresponding Nutri-Scores; Feedback and fixation-based fixation dots were implemented **c)** Experimental procedures; blue refers to sated, yellow to hungry condition (order counterbalanced). VAS refers to visual analogue scale used to assess subjective feelings of hunger. PANAS refers to a questionnaire assessing mood (see *SOM1*). FEV II refers to a questionnaire assessing eating behavior (see *SOM2*); *indicates that these steps were only required in the first session.

Results

Hunger state manipulation

First, we tested whether the manipulation of hunger state was successful (**Figure 2a**). Upon arrival at the lab, participants' hunger ratings did not differ between the sated condition ($M_{sated\ t1}=51.98$, $SD_{sated\ t1}=27.54$) and the hungry condition ($M_{hungry\ t1}=57.99$, $SD_{hungry\ t1}=23.27$, $t(63)=-1.265$, $p=.211$, $d=0.159$). The RM-ANOVA indicated that the change in hunger ratings between the last and first time point differed across conditions ($F(1)=26.31$ $p<.001$, $d=0.708$). Specifically, in the hungry condition the change was positive, meaning participants got hungrier throughout the experiment ($M_{hungry\ diff}=22.4$, $SD_{hungry\ diff}=20$), whereas in the sated condition this difference was negative ($M_{sated\ diff}=-36.3$, $SD_{sated\ diff}=31.3$). Thus, our hunger state manipulation had the desired effect on the subjective feeling of hunger. Notably, there were no effects of hunger state on positive and negative affect across timepoints (*Figure S1*).

Effect of hunger state on choice and RT

In both conditions, a larger value difference (VD) with respect to taste was predictive of tasty choice (**Figure 2c**), while a larger VD with respect to health was predictive of healthy choice, particularly in the sated condition (**Figure 2d**). The GLMM of choice (tasty vs. healthy) indicated that overall participants preferred tasty over healthy options ($\beta_{intercept}=0.73$, $SE=0.098$, $p<.001$). In line with our preregistered hypotheses, we found that, participants were less likely to choose the tasty option when being sated as compared to hungry ($\beta_{sated}=-0.211$, $SE=0.103$, $p=.04$). Moreover, longer relative dwell time on the chosen option increased the likelihood of choosing that option ($\beta_{dwell\ time}=0.998$, $SE=0.027$, $p<.001$) (**Figure 3a**) (see *Table S1* for model specifications, random effects and an alternative model with additional predictors).

Importantly, we assessed the robustness of our findings by testing alternative GLMMs to predict choices, in which we replaced the taste / health ratings as predictors by wanting / health ratings (*SOM4*, *Table S3*) and by high / low caloric information (*SOM5*, *Table S4*). Of note, replacing tastiness ratings by wanting ratings as predictor led to even stronger effects of hunger on choice (*Table S3*, *Figure S4*). Furthermore, we performed a principal component analysis (PCA) to demonstrate that these different measures are linked to participants' decisions by two main components that represent health and taste aspects, respectively (*Figure S8*, *Table S11*), and that explain almost 80% of the variance in dietary decisions.

With respect to response time (RT), we found that RT was highest for choices in which taste ratings were similar for both options (**Figure 2e**), while health value did not affect RT (**Figure 2f**). The GLMM of RT indicated an average RT of 2.748s ($SE=0.096$). Tasty choices were associated with faster decisions, decreasing RT by 0.15s ($SE=0.018$, $p<.001$). Longer relative dwell time predicted slower choice in general ($\beta_{dwell\ time}=0.065$, $SE=0.014$, $p<.001$), but was sped-up for tasty choices ($\beta_{dwell\ time*tasty\ choice}=-0.13$, $SE=0.017$, $p<.001$) (see *Table S2* for model specifications, random effects and an alternative model with additional predictors).

Altogether, we found that participants preferred tasty over healthy options, and that this preference was amplified under hunger. While tasty choices were faster in general, we did not find an effect of hunger state on RT. Finally, our GLMMs indicate that dwell time is an important predictor of choice and RT.

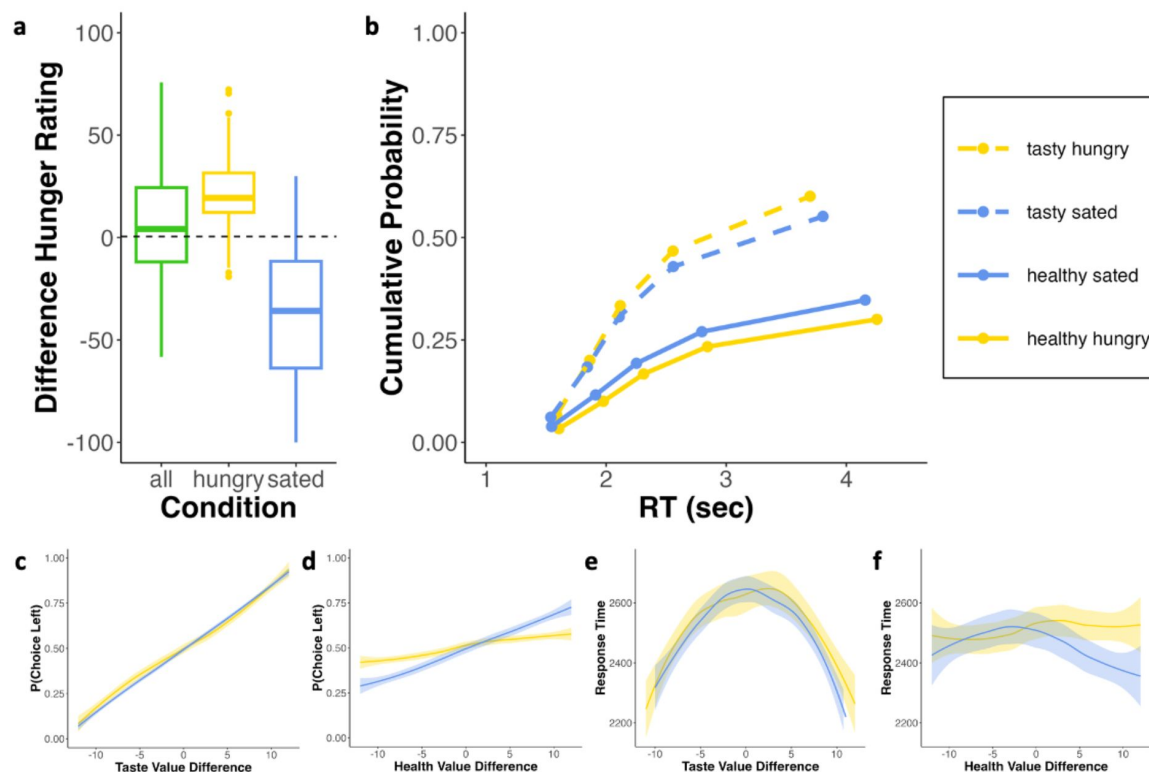


Figure 2

Behavioral Results

a) Manipulation check: The green boxplot displays the difference (hungry-sated) in hunger state at arrival at the lab, yellow and blue boxplots display the difference (last timepoint-first timepoint) in hunger state in the hungry and sated condition, respectively. **b)** RT quantile plot displaying the cumulative probability of tasty (dashed lines) and healthy choices (solid lines) separately for the two conditions (quantiles are .1, .3, .5, .7, .9 of choices). **c)** and **d)** Probability to choose the left option as a function of taste and health value difference (left/right), respectively. Importantly, the dependency of choice on health information was eliminated under hunger. **e)** and **f)** Corresponding mean RTs as a function of taste and health value difference, respectively. For illustration purposes, value differences were segmented into 25 bins, and a locally weighted scatterplot smoothing technique was applied with a span of 0.75. Plots **c-f)** are based on all trials. Transparent shades indicate the standard errors of the smoothed choice probability and RT for the respective value bins (see also *Figure S5*).

Hunger affects attention and dietary choice

In line with previous work (Gluth et al., 2018 [↗](#); Krajbich et al., 2010 [↗](#); Weilbächer et al., 2021 [↗](#); Yang & Krajbich, 2023 [↗](#)), the previous analyses indicate that looking longer at one option was positively associated with the likelihood of choosing that option. This effect was observed in both conditions to a very similar degree (**Figure 3a** [↗](#)). When analyzing dwell time on the attribute level, however, there was a significant condition difference: Although participants were much more likely to look at food images (taste attribute) than the Nutriscores (health attribute) in both conditions, this difference was even more pronounced in the hungry compared to the sated state ($t(69)=2.595$, $p=.006$, $d=0.312$; **Figure 3b** [↗](#)). This effect remained significant after excluding outlier data ($t(68)=2.392$, $p=.01$, $d=0.29$). First and last fixations and transition patterns are documented in *Figure S6*.

The analyses so far suggest that dwell time depends on hunger state (**Figure 3b** [↗](#)) and is predictive of choice (**Figure 3a** [↗](#)). To better understand these interactions, we conducted a hierarchical Bayesian mediation analysis testing whether attention (i.e., dwell time) mediates the relationship between hunger state and food choice (**Figure 3c** [↗](#), *Tables S5-S6*). In line with our GLMM on choice, the direct path between hunger state and food choice was significant ($M_c=0.27$, $SE_c=0.12$, $CI_c=[0.03, 0.52]$), meaning hungry individuals were more likely to choose tasty options. Similarly, the path between attention and food choice was significant ($M_b=5.41$, $SE_b=0.45$, $CI_b=[4.54, 6.32]$), indicating that longer dwell times on one option were predictive of choosing that option. Furthermore, there was a small yet significant relationship between hunger state and attention ($M_a=0.01$, $SE_a=0.01$, $CI_a=[<0.001, 0.022]$), demonstrating that hungry individuals paid relatively more attention to chosen options. Critically, our mediation analyses revealed that the direct path between hunger state and food choice was no longer significant when attention was considered ($M_{cp}=0.19$, $SE_{cp}=0.11$, $CI_{cp}=[-0.02, 0.41]$), while the population-level mediation path ($a*b$) was significant ($M_{a*b}=0.08$, $SE_{a*b}=0.04$, $CI_{a*b}=[0.01, 0.16]$). Alternative mediation models (with wanting ratings or caloric information are reported in *Tables S7-S10*).

Altogether, the eye-tracking analyses demonstrated that attention was predictive of choice, and hungry participants' preference for tasty foods was reflected in their dwell time. Finally, attention emerged as a pivotal mediator of the relationship between hunger state and food choice.

Mechanisms underlying the effect of hunger on attention and dietary choice

In line with our hypotheses, we found that participants were more likely to choose tasty over healthy food items, and this difference was amplified by hunger (**Figure 2b** [↗](#)). Moreover, we demonstrated that attention mediated the effect of hunger on choice (**Figure 3c** [↗](#)). To further elucidate the cognitive processes underlying these effects, we estimated and compared different versions of DDMs against one another using hierarchical Bayesian cognitive modeling. Models varied in terms of whether and how they accounted for attention, whether a starting point bias (towards tasty vs. healthy options) was included, and whether a parameter that allows different latencies of taste and health information on the drift rate was included (see *Methods*).

Initial model comparison revealed that *i*) there was no evidence for a starting point effect (models without starting point consistently outperformed models with starting point), *ii*) there was no evidence for different latencies of taste and health information (parameter estimates consistently overlapped with 0), and *iii*) that the multi-attribute attentional DDM (maaDDM), which allows modeling discounting of unattended options as well as unattended attributes, outperformed simpler variants (i.e., DDM, aDDM) (**Table 1** [↗](#)).

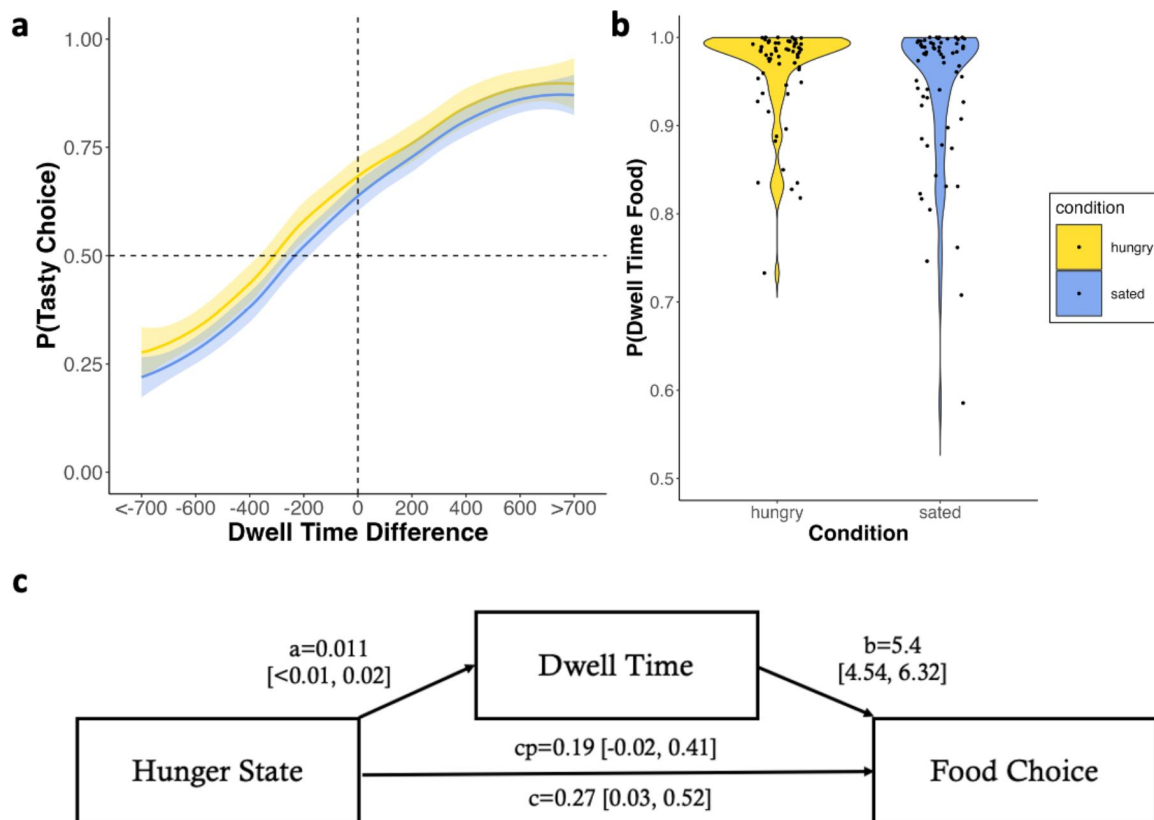


Figure 3

Eye-Tracking Results

a) Dwell time difference between the tasty and healthy option was positively associated with the probability of choosing the tasty option in both conditions. **b)** The average probability to look at food image (taste attribute) compared to Nutri-Score (health attribute) was even higher in the hungry than sated condition. **c)** Path diagram with posterior means of the parameters, associated 95%-credible interval in squared brackets.

Table 1

Quantitative Model Comparison

Model	α	nDT	d	ω	β	θ	ϕ_1	ϕ_2	rst	DIC	Rhat
DDM	YES	YES	YES	YES	NO	NO	NO	NO	NO	69646	1.002
DDMsp	YES	YES	YES	YES	YES	NO	NO	NO	NO	69668	1.004
mtDDM	YES	YES	YES	YES	NO	NO	NO	NO	YES	69138	1.056
aDDM	YES	YES	YES	YES	NO	YES	NO	NO	NO	65561	1.004
aDDMsp	YES	YES	YES	YES	YES	YES	NO	NO	NO	65587	1.003
maaDDM	YES	YES	YES	YES	NO	YES	YES	NO	NO	65155	1.005
maaDDMsp	YES	YES	YES	YES	YES	YES	YES	NO	NO	65214	1.011
maaDDM2ϕ	YES	YES	YES	YES	NO	YES	YES	YES	NO	64002	1.017
maaDDM2 ϕ sp	YES	YES	YES	YES	YES	YES	YES	YES	NO	65070	1.027

Further inspection of differences in the maaDDM's parameter estimates between the hungry and sated conditions suggested that hunger increased the weight of taste information relative to health information and exacerbated attribute-wise attentional discounting (i.e., lower estimates of parameter ϕ (Figure S14). To shed more light on this attentional effect of hunger, we tested an extension of the maaDDM that assumed two separate attribute-wise discounting parameters for taste and health information (i.e., maaDDM2 ϕ). Remarkably, this model provided a much-improved model fit compared to the maaDDM and all other models (Table 1). Moreover, the posterior predictive checks of this model indicated that it provides an exquisite account of the choice and RT data (Figure 4). Again, we assessed the robustness of our results by also testing additional models in which health and taste attributes were replaced by Nutri-Scores (Table S12; Figures S22-S30) and wanting (Table S13; Figures S31-S34), respectively. Importantly, these supplementary modeling analyses yielded comparable quantitative and qualitative results.

Taking a closer look at the group parameter distributions of the winning model (i.e., maaDDM2 ϕ), we found that participants' relative taste weight was larger than .5 in both conditions, indicating a higher taste compared to health preference ($HDI_{sated}=[0.698, 0.831]$; $HDI_{hungry}=[0.788, 0.922]$). Critically, this preference was credibly higher under hunger ($HDI=[0.122, 0.642]$; Figure 5a). We did not find differences between conditions with respect to the drift scaling parameter d ($HDI=[-0.165, 0.025]$; Figure 5b), the non-decision time nDT ($HDI=[-0.02, 0.087]$; Figure 5c), or the boundary separation a ($HDI=[-0.12, 0.18]$; Figure 5d). Similarly, there were no credible hunger effects with respect to the attentional discounting of the options θ ($HDI=[-0.092, 0.017]$; Figure 5e). Looking at the two attribute-wise attentional discounting parameters revealed that there was no condition effect on discounting of the taste attribute (i.e., ϕ_T , $HDI=[-0.291, 0.16]$; Figure 5f), but instead, hunger exclusively increased the discounting of health information (i.e., ϕ_H , $HDI=[-1.088, -0.188]$; Figure 5g).

Taken together, our extension of the multi-attribute attentional DDM with separate attention parameter for taste and health attributes (i.e., maaDDM2 ϕ) provided the best quantitative and an excellent qualitative account of the data, and it suggests that hunger affects the relative weighting of taste compared to health information and further increases the discounting of unattended health information during the evidence-accumulation process.

Discussion

The goal of this study was to elucidate the mechanisms driving dietary choice under hunger. We found that individuals prefer tasty over healthy food options, and that this preference is amplified by hunger state. This pattern was also reflected in our modeling analyses, revealing that taste was weighted more than health in both, but especially in the hungry condition. Our mediation analysis suggests that the cognitive mechanism underlying the influence of hunger state on food choice is driven by a shift in attention. Specifically, hungry individuals pay more attention to tasty food options in general and the taste attribute in particular, which in turn increases the probability of tasty choices. Again, our cognitive modeling analyses integrated these findings, demonstrating increased attentional discounting of the health attribute under hunger. Together our findings suggest a nuanced interplay between attention and the significance assigned to the options' underlying attributes in dietary decision making.

First, in line with previous research (Cheung et al., 2017; Otterbring, 2019; Read & van Leeuwen, 1998) we demonstrate that hunger affects dietary choice. Participants were more likely to choose options that were more tasty than healthy, that they reported higher wanting for, and that contained higher caloric content. Moreover, our findings indicate that higher taste ratings were strongly predictive of choice across conditions, whereas higher health ratings only predicted choice in the sated condition, albeit less influential than taste ratings (Figure 2c,d). Crucially, our modeling analyses endorsed this account: across models we demonstrate that the relative

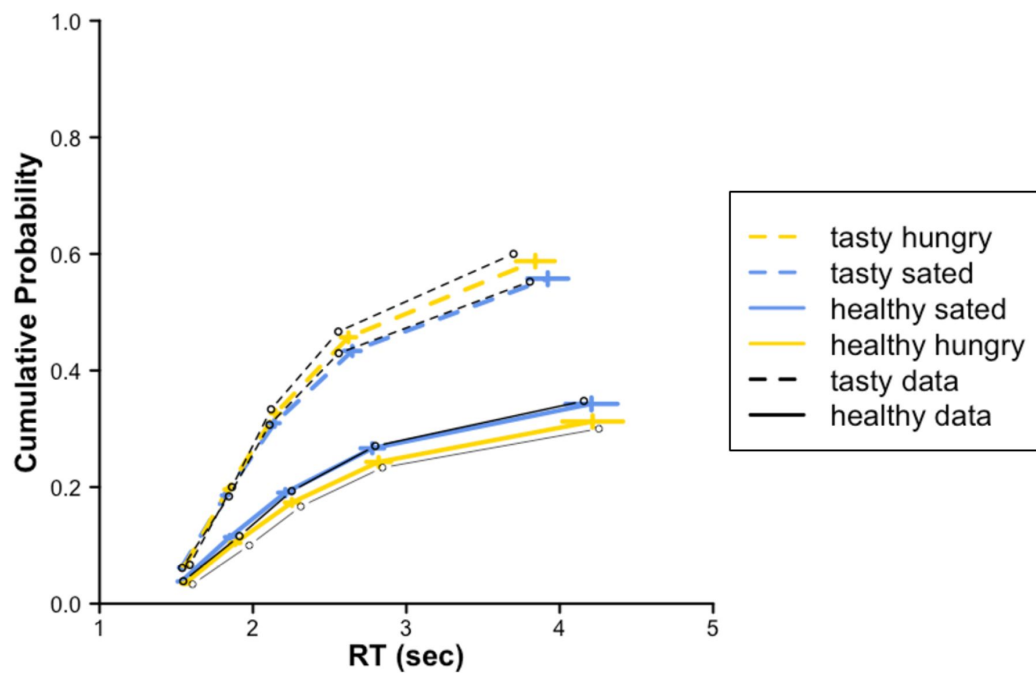


Figure 4

Posterior Predictive Checks $\text{maaDDM2}\phi$

Quantile plots of simulated data with fitted parameters of the $\text{maaDDM2}\phi$ in blue (sated) and yellow (hungry) with HDIs of each quantile (vertical lines) and behavior. Posterior predictive checks were performed by drawing 1000 parameter values from the individual posterior parameter distribution to simulate the new data.

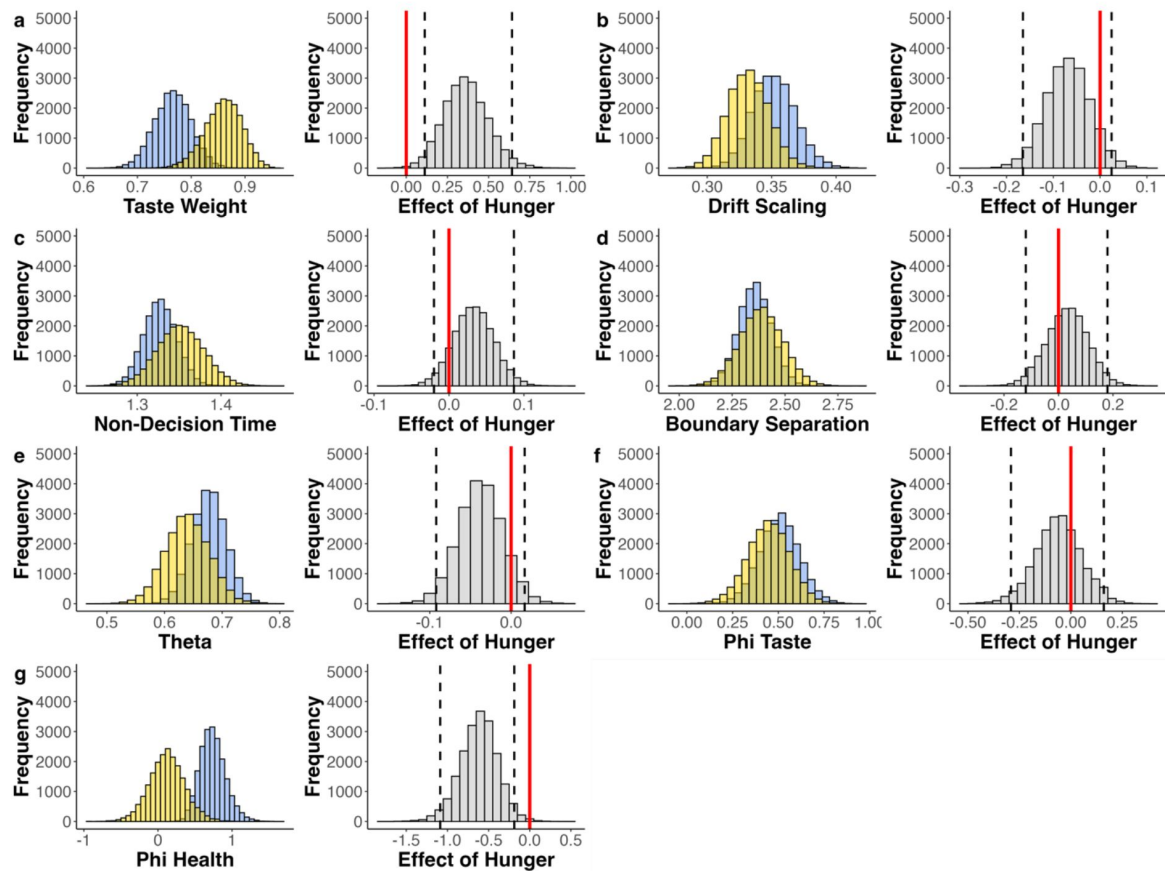


Figure 5

Parameter estimates of maaDDM2 ϕ

Group parameter estimates (blue = sated, yellow = hungry; left panels) and the effect of hunger state (gray; right panels). Dashed black lines indicate the 95% HDI. **a)** Estimated taste weights. In both conditions the weight is larger than .5, indicating a higher weight on taste compared to health. This preference was even stronger under hunger. **b-f)** Parameter estimates of d , nDT , α , θ and ϕ_T , and the corresponding effects of hunger state. **g)** Parameter estimates of ϕ_H and the corresponding effects of hunger state, showing that the attention-driven discounting of health information was amplified under hunger.

taste weight was larger in both conditions and particularly in the hungry condition. This finding adds to previous work demonstrating the distinct influence of taste and health attributes in guiding choice (Barakchian et al., 2021 [↗](#); Enax et al., 2016 [↗](#); Hutcherson & Tusche, 2022 [↗](#); Maier et al., 2020 [↗](#); Rramani et al., 2020 [↗](#)), by illustrating that these effects can differ across states. This also aligns with results from a food bidding task (Fisher & Rangel 2013 [↗](#)), wherein the authors find that hunger elevated the bids and speculate that this effect was driven by an increased taste but not health valuation of food items.

Second, we show that the valuation is not only influenced by the attributes underlying decision weights, but moreover by attention. Behaviorally, we show that attention mediates the impact of hunger state on food choice, such that hunger state predicts overall less dwell time on the healthy option, thereby increasing the probability of tasty choice. Upon closer examination of attention allocation to the respective attributes, we show that participants, especially when hungry, spent much more time on food images compared to Nutri-Scores. We see two explanations for the excessively high proportion of dwell time on food images compared to Nutri-Scores: First, food images were more important for deciding, as indicated by the relative weight parameter being larger than .5. Consequently and in line with previous work (Orquin et al., 2021 [↗](#)), people pay more attention to more important attributes. Second, food images contain more complex of information. Whereas extracting taste information from a food image can be seen as a complex inference process, a (color-coded) nutritional score provides salient and easily discernible evidence about a product's healthiness and consequently requires less dwell time. This account is supported by studies showing that nutritional scores can promote healthy choice despite proportionally little dwell time (e.g., Bialkova et al., 2014 [↗](#); Gabor et al., 2020 [↗](#); Rramani et al., 2020 [↗](#)).

To take these putatively different attentional demands of different attributes into account, we extended the maaDDM of Yang and Krajbich (2023) [↗](#) and developed the maaDDM2 ϕ , which assumes separate discounting parameters for separate (unattended) attributes. Consistent with the above-mentioned attribute-specific effect of hunger on choices, we found that the attentional discounting of the health attribute but not the taste attribute was amplified under hunger, such that unattended nutritional information had a blunted influence on the evidence accumulation process. Notably, we also found a hunger effect on the attribute discounting parameter ϕ in the regular maaDDM (Figure S14) but our extension allowed us to pinpoint this effect specifically to health information. Given related work on the malleability of attentional discounting on mnemonic demands (Eum et al., 2023 [↗](#); Weilbacher et al., 2021 [↗](#)), we speculate that hunger could impede a person's ability or willingness to maintain health considerations in working memory when attention is currently drawn to the tasty food stimulus.

Several supplementary analyses demonstrate the robustness of our findings. In essence, and in line with a large body of literature (e.g., Garlasco et al., 2019 [↗](#); Otterbring, 2019 [↗](#); Read & van Leeuwen, 1998 [↗](#)), hungry participants were more likely to choose items which they rated higher in terms of tastiness, wanting and caloric content. Importantly, the pivotal role of attention was also established in the exploratory wanting and calorie analyses (SOM). Moreover, we performed a PCA to identify the major components that drive food choices, finding that two factors representing tastiness and healthiness aspects explain 81% of the variance in the data. We see this as a justification to describe and study dietary choices by means of these two attributes, essentially following a series of previous studies in our field (e.g., Hutcherson & Tusche, 2022 [↗](#); Maier et al., 2020 [↗](#); Rramani et al., 2020 [↗](#); Sullivan & Huettel, 2021 [↗](#)).

Although mediation and cognitive modeling analyses are limited with respect to inferring causality, our results clearly suggest a critical role of attention in guiding choice, stipulating that healthy choice may be promoted by increasing attention to healthy options and attributes. This has been investigated for example in behavioral (Barakchian et al., 2021 [↗](#); Bucher et al., 2016 [↗](#); Cheung et al., 2017 [↗](#); Sullivan & Huettel, 2021 [↗](#)), eye-tracking (Schomaker et al., 2022 [↗](#); Vriens et

al., 2020 [↗](#)) and neuroimaging studies (Hare et al., 2011 [↗](#); Hutcherson & Tusche, 2022 [↗](#)) showing that focusing attention on health aspects increased healthy choice. For example, Hutcherson and Tusche (2022) [↗](#) compellingly demonstrated that the mechanism through which health cues enhance healthy choice is shaped by increased value computations in the dorsolateral prefrontal cortex (dlPFC) when cue and choice are conflicting (i.e., health cue, tasty choice). In the context of hunger, these findings together with our analyses suggest that drawing people's attention towards health information will promote healthy choice by mitigating the increased attentional discounting of such information in the presence of tempting food stimuli.

In conclusion, our study provides substantial insights into the mechanism underlying dietary choice across metabolic states. Our extension of the multi-attribute attentional DDM analyses revealed that the valuation of food options under hunger is compromised by a relatively lower weighting and a stronger attentional discounting of health information. This modeling extension is a general contribution to advance research on multi-attribute decision making, as it allows modeling attribute-specific attentional discounting, which is likely to occur if attributes are described in markedly different formats.

Methods

Preregistration

The study was preregistered on Open Science Framework (osf.io/tmdw3). An a-priori power analysis was conducted to determine the required sample size of the experiment using G*Power (Faul et al., 2009 [↗](#)). The power analysis was targeted on testing an effect of hunger on non-food choices (which were part of the same study but are not reported here). A study by Skrynka & Vincent (2019) demonstrated that hunger state affected the discounting of food and other commodities, for which the authors report very large and medium-large effect sizes, respectively. Given inflated effect sizes due to publication bias (Simonsohn, 2015 [↗](#)), we set our smallest effect size of interest (Lakens et al., 2018 [↗](#)) to Cohen's $d = 0.3$, with an alpha level of .05, and a power of .8, resulting in a required sample size for a one-tailed paired t-test of 70 participants. In line with Skrynka & Vincent (2019), we expected a larger effect of hunger on food choices (i.e., $d = 0.5$) and thus consider the current experiment being sufficiently powered.

Participants

A total of 70 participants (53 females, 16 males and 1 diverse, $M_{age} = 25.6$, $SD_{age} = 8.064$, $M_{BMI} = 23.224$, $SD_{BMI} = 4.363$) completed both sessions of the experiment. Participants were recruited from the University of Hamburg using its only recruiting system SONA ($n = 40$) and Stellenwerk (stellenwerk-hamburg.de) ($n = 30$) and received course credits or monetary compensation (€12.50 per hour). Individuals were eligible to participate in the study if they were proficient in German and were at least 18 years old. Exclusion criteria included dietary-related aspects (e.g., diets, vegan, food allergies, and intolerances), physical or mental illnesses, drug use, pregnancy, and breastfeeding. The Local Ethics Committee of the Faculty of Psychology and Human Movement Sciences at the University of Hamburg approved the study.

Procedure

Before participants signed up for the study a questionnaire was acquired to assess participants' eligibility and collect demographic information. The latter was used to compute the amount of protein shake participants received in the sated condition (see *Hunger state manipulation*). Hunger state was counterbalanced such that $n = 36$ completed the experiment in the hungry condition first and $n = 34$ in the sated condition first. In the first session, participants were informed about the procedure and provided their informed consent. In both sessions, participants first rated their subjective feeling of hunger (see *VAS*) and mood (see *SOMI*). In the sated condition, participants

received a protein shake matched to their daily caloric needs (see *Hunger state manipulation*) and rated hunger and mood again. In both sessions, the experiment started with a rating task, followed by hunger and mood ratings, then the choice tasks, and concluded with subsequent hunger and mood ratings before reaching the reward screen (**Figure 1c**). At the end of the first session, participants filled out a questionnaire assessing eating behavior (see *SOM2*). Finally, participants were compensated and received their reward. Overall, one session lasted for approximately 2h. The second session took place 5–10 days ($M=7.915$, $SD=2.755$) after the first.

Hunger state manipulation

In both conditions participants came to the lab after an overnight fast. In the sated condition participants received an individually determined amount of whey protein shake from MyProtein (myprotein.com) (flavor: vanilla, or strawberry) amounting to 25% of participants' daily caloric needs in line with Schofield equations (Schofield, 1985). The equation considers gender, age, weight, and activity level, which was set to 1.4 ("sedentary") for all participants, in line with Wever et al. (2021).

Experimental tasks and materials

The experiment was implemented in OpenSesame version 3.3 (Mathôt et al., 2012), and PyGaze (Dalmaijer et al., 2014) was used for the implementation of different eye-tracking functions. Participants completed the experiment on a 24-inch screen with a resolution of 1024×768 pixels. The experiment consisted of three counterbalanced rating blocks, and corresponding choice blocks (i.e., food preference and choice, social preference and choice, intertemporal preference and choice). Here, we report the results of the food rating and food choice task only. The social and intertemporal ratings and choices will be reported separately. Stimuli of the food tasks were taken from the Full4Health Image Collection and included 66 standardized images of food presented on a plate (Charbonnier et al., 2016, available at osf.io/cx7tp/). Food images were selected based on their familiarity in Germany, and matched with respect to the Nutri-Score, which represents a rating of the nutritional quality of a food item within a product category (from A = balanced nutrition to E = unbalanced nutrition, Federal Ministry of Food and Agriculture). While familiar in Germany and other European countries, participants were also informed about meaning of the Nutri-Score before the experiment started. We included 13 food images of Nutri-Scores A and B each with approximately half sweet (e.g., kiwi) and half savory (e.g., cucumber); 12 food images of Nutri-Score C each half sweet (e.g., dried apricots) and half savory (e.g., olives); and 14 images of Nutri-Scores D and E each with approximately half sweet (e.g., Oreo biscuits) and half savory (e.g., Potato Crisps). Food images (387.2×259.2px) and corresponding NutriScores (166.5×94.1px) were displayed in both rating and choice task. The position of the images was counterbalanced, such that for half the participants, the Nutri-Score was displayed on the upper part of the screen and the food image on the lower part, while for the other half of the participants, the positions were reversed. A grey background (#777777) was used for the entire experiment.

Food rating task

Participants were asked to rate all 66 food images on a continuous scale using the mouse to move the slider and mouse button to log their response (**Figure 1a**). The initial position of the slider was in the center of the scale. Food images appeared after a white fixation dot (1000ms) in random order. Overall, participants rated items on four scales indicating perceived tastiness ("How tasty would you rate this item? Not tasty at all – very tasty"), healthiness ("How healthy would you rate this item? Not healthy at all – very healthy"), wanting ("How much would you like to eat this item at the end of the experiment? Not at all – very much"), and perceived caloric content ("How high would you rate the caloric content of this item? Very low–very high"). Text and slider were white. No time limit was imposed in this task.

Food choice task

In the binary food choice task, participants were asked to select the food image they preferred, knowing that they would be incentivized in line with their choices (see *Incentivization*). Overall, participants made 190 choices per session, including a self-paced break halfway through the task. During the task participants' eye-movements were recorded (see *Eye-tracking data*). One trial consisted of a white fixation dot (i.e., participants had to fixate the dot for 1000ms before the trial began, which ensured calibration at each trial), the option screen (self-paced) and a feedback screen (500ms). The option screen included two food images and their corresponding Nutri-Scores, in counterbalanced positioning. As for the feedback, a black frame was implemented around the chosen option (**Figure 1b**). This part of the experiment took approximately 25min.

Visual Analogue Scale (VAS)

A VAS (Sepple & Read, 1989) was used to assess subjective feeling of hunger and fullness (i.e., “how hungry/ full are you?”) on a continuous scale ranging from “0 = not hungry/ full at all to 100 = very hungry/ full” (Parker et al., 2004).

Other control measures

Demographic information including gender, age, weight, height, handedness, level of education, and monthly disposable income were recorded before the experimental sessions. In both experimental sessions additional questions concerning participants last meal and usual breakfast routines were collected. If applicable, women also answered questions with respect to their menstrual cycle. Throughout each session, we assessed participants' mood (see *SOM1, Figure S1*. At the end of the first session, we also assessed eating behavior (see *SOM2, Figure S2*).

Incentivization

To ensure ecological and external validity (Barakchian et al., 2021) during the choice task, participants received a food item for which they indicated a preference of at least 50 in the food rating task and had chosen in a randomly selected trial in the choice task, at the end of each session. We stored the 66 food items in shelves and a fridge in our lab. After each testing session, inventory was assessed, and stores were refilled.

Eye-tracking data

During the choice tasks, participants' fixation patterns were recorded using a SR Research EyeLink 1000 Plus eye-tracker for high-quality recording of eye movements and pupillometry with up to 2kHz sampling rate. A chin rest was used to avoid head movements of the participants and subsequent recalibrations. The distance between screen and chin rest was approximately 93cm. The eye-tracker was calibrated at the beginning of each choice task and after completing half of the trials.

Preprocessing of eye-tracking data was performed in Matlab (2021b, mathworks.com) using the edfmex converter (SR Research Ltd.). Preprocessing included parsing the events into trials and locations. Areas of interest (AOI) were the four positions on the screen, where food images and Nutri-Scores were displayed. We increased these areas by 5% of their original size. Preprocessing resulted in two data-frames per participant: one in which the length corresponded to the number of trials and fixation durations and the different AOIs were summed within (for multiple fixations at one location) trials; the length of second data-frame corresponded to the total number of fixations of all trials of each participant in each condition.

Data analysis

In line with our preregistration, RTs were preprocessed before further analyses by excluding trials that were >4 SD above the individual mean RT per condition or <250 ms. As we had a different number of hunger ratings between conditions (participants rated their hunger three times in the hungry and four times in the sated condition; see [Figure 1c](#)), we evaluated the effectiveness of our hunger state manipulation with a RM-ANOVA on the difference scores in hunger rating (i.e., last timepoint–first timepoint) with condition as a within-subject factor and a paired t -tests to assess differences in hunger ratings at lab arrival. Participants' hunger ratings did not entail extreme outliers, and a Shapiro-Wilk test suggested that hunger ratings were normally distributed. Due to missing values for one timepoint in six participants [these participants did not fill in the VAS and PANAS before the administration of the Protein Shake in the sated condition], the analyses of the hunger state manipulation had a sample size of 64. Reported values include F - and t -statistics, (Bonferroni-corrected) p -values and effect sizes based on Cohen's d .

In line with our preregistration, analyses of the food choice task were focused on trials in which one option was rated higher in taste and lower in health compared to the other option (i.e., conflict choices). There were on average 75.68 ($SD=21.96$) of these trials per participant. The main analyses comprised two types of generalized linear mixed models (GLMM) using the lme4 package ([Bates et al., 2015](#)) in R (version: 4.3.1). First, we implemented a mixedeffects logistic regression analyses with tasty vs. healthy choice (*SOM3, Table S1*) as binary outcome with a binomial distribution and a logit link function (see also *SOM4, Table S3* for analyses of wanting vs health and *SOM5, Table S4* for analyses of high caloric versus low caloric choice); second, we implemented a mixed effects regression analyses with RT as dependent variable and a Gamma distribution with an identity link function (*Table S2*). In both analyses, models with random intercepts for each participant and random slopes for condition ($AIC_{GLMM2\ choice}=13017.95$, $AIC_{GLMM2\ RT}=23438.93$) outperformed models without random effects ($AIC_{GLM\ choice}=13845.4$, $AIC_{GLM\ RT}=24556.97$) and those with random intercepts only ($AIC_{GLMM1\ choice}=13216.59$; $AIC_{GLMM\ RT}=28544.95$). The buildup and comparison of the different models is specified in *SOM3*. In line with our preregistration, we included condition (hungry vs sated) and attention (relative dwell time difference of chosen - unchosen option) as predictors (*Table S2a*). Exploratory models including demographic information as well as scores on participants mood and eating behavior are reported in *Table S2b-c*. For the RT model we used the same predictors as in our choice model with “choice” (tasty vs healthy) as an additional predictor. Reported values include correlation coefficients, standard errors (SE), z - and p -values.

The eye-tracking analyses was implemented on conflicting trials (i.e., one option was tastier compared to the other option). The analyses included a paired t -tests for the difference in relative dwell time on attribute between conditions and a Bayesian within subject multilevel mediation analyses ([Vuurre & Bolger, 2018](#)) with choice (tasty vs. healthy) as dependent variable, hunger state as independent variable, and relative dwell time to chosen option as mediating variable, using the bmlm package in R ([Vuurre, 2023](#)). Reported values include t -statistics, p -values and effect sizes based on Cohen's d for the t -test, as well as correlation coefficients, SEs and credibility intervals (CI) for the mediation analysis. Convergence for the mediation analysis was assessed via the Gelman-Rubin statistic (“Rhat”) ([Gelman & Rubin, 1992](#)) with a threshold of 1.05 ([Vuurre & Bolger, 2018](#)).

Cognitive Models

To elucidate the cognitive mechanisms underlying the interaction of attention and decision making in dietary choice, we preregistered to use the multi-attribute time-dependent Drift Diffusion Model (mtDDM) ([Maier et al., 2020](#); [Sullivan & Huettel, 2021](#)) and extend it with attention-related parameters for both options ([Krajibich et al., 2010](#)) and attributes. The core assumption of the mtDDM is that different attributes enter the choice process at different times

(e.g., taste information before health information). However, our modeling analyses quickly revealed that there was little to no support for different onset times of the two attributes (see **Table 1** and *Figure S11*). Therefore, our modeling analyses focused on models incorporating attentional dynamics, and we refrained from further developing the mtDDM model.

We had six different measures of the presented food stimuli, including subjective ratings of tastiness, wanting, healthiness and caloric content, as well as objective characteristics such as Nutri-Score and objective total caloric content. These measures were highly correlated (*Figure S7*). Therefore, we conducted a Principal Component Analysis (PCA) using the R package ‘FactoMineR’ (Lê et al., 2008). The PCA included the standardized value differences (left – right) of each of our measures. Results revealed that 81% of variance was explained by two components, the first loading positively on caloric information (subjective and objective) and negatively on health information (subjective rating and Nutri-Score), while the second one loaded positively on taste and wanting (*Figure S8*; *Table S11*). This suggests that there are two main factors influencing food choice, one reflecting health aspects (higher health and nutrition rating and lower calories), while the other represents taste aspects. Importantly, loadings of taste measures on the health component and loadings of health measures on the taste component were low suggesting independence of these factors (see also *Figure S3*). Consequently, we limited our modeling analyses to two attributes reflecting health and taste respectively.

The computational models were fit to choices and RT of all (pre-processed) trials. In case of DDMs that included attentional dynamics, eye-tracking data was used to inform the model (see below). Overall, we tested 9 different versions of DDMs, all of them including boundary separation (a), non-decision time (nDT), and a drift scaling parameter (d) as free parameters [note that attentional DDMs are often estimated with a being fixed and the standard deviation of the drift being a free parameter; here, we followed the convention in the larger DDM community, and estimated a while fixing the standard deviation to 1]. The definition of the drift rate varied across models, and the (relative) starting point (β) was either fixed to 0.5 or estimated. For the most basic Drift Diffusion Model (DDM), the drift rate was determined by multiplying the scaling parameter d with the value difference (VD) which was given by the taste (T) and health (H) differences [taste and health values were scaled in line with Yang and Krajbich 2023, such that they would be between one and ten using a generalized distance function (Berkowitsch et al., 2015)] of the two options i and j , weighted by the free parameters ω (relative taste weight) and $1 - \omega$ (relative health weight), respectively ($0 \leq \omega \leq 1$).

$$VD = \omega(T_i - T_j) + (1 - \omega)(H_i - H_j) \quad (1)$$

The second model was the mtDDM, in which VD also depended on taste weight ω and health weight ($1 - \omega$), but these weights were allowed to start influencing the choice process at different points in time (here: relative starting time; rst). A positive rst implies an earlier onset for taste, a negative rst implies an earlier onset for health (for more details see: Barakchian et al., 2021; Maier et al., 2020; Sullivan & Huettel, 2021). The third model was an attentional DDM (aDDM) (Krajbich et al., 2010), which included (next to ω) the relative dwell time on each option and parameter θ , which models a dependency of VD on the (dwell) time spent on each option. Specifically, the VD in favor of option i relative to option j depends on the dwell time (f) on the options as follows:

$$VD = f_i (\omega(T_i - \theta T_j) + (1 - \omega)(H_i - \theta H_j)) + f_j (\omega(\theta T_i - T_j) + (1 - \omega)(\theta H_i - H_j)) \quad (2)$$

The fourth model, the multi-attribute attentional DDM (maaDDM) included two attentional parameters to discount the non-looked upon option (θ) and attribute (ϕ), respectively. Thus, VD is defined as follows:

$$VD = f_{i,T}(\omega(T_i - \theta T_j) + (1 - \omega)\phi(H_i - \theta H_j)) + f_{i,H}(\omega\phi(T_i - \theta T_j) + (1 - \omega)(H_i - \theta H_j)) + f_{j,T}(\omega(\theta T_i - T_j) + (1 - \omega)\phi(\theta H_i - H_j)) + f_{j,H}(\omega\phi(\theta T_i - T_j) + (1 - \omega)(\theta H_i - H_j)) \quad (3)$$

Finally, we developed and tested an extension of the maaDDM of Yang and Krajbich (2023) with two separate ϕ parameters for taste (ϕ_T) and health (ϕ_H) (maaDDM2 ϕ). The rationale behind the extension is, that in our study (but also other related studies), the attributes representing taste and health differed with respect to image complexity, size and informational content and consequently might differ with respect to their rate of discounting. For the maaDDM2 ϕ , the VD is thus given by:

$$VD = f_{i,T}(\omega(T_i - \theta T_j) + (1 - \omega)\phi_H(H_i - \theta H_j)) + f_{j,T}(\omega(\theta T_i - T_j) + (1 - \omega)\phi_H(\theta H_i - H_j)) + f_{i,H}(\omega(\phi_T T_i - \theta T_j) + (1 - \omega)(H_i - \theta H_j)) + f_{j,H}(\omega\phi_T(\theta T_i - T_j) + (1 - \omega)(\theta H_i - H_j)) \quad (4)$$

For each of these five models, we tested two versions which either allowed the relative starting point parameter (β) to be free or fixed it to 0.5. Models with fixed β consistently provided a more parsimonious account of the data. In addition, we also tested models in which the drift rate was informed by the scaled VD of taste and Nutri-Score (Table S12, Figures S22-S30) wanting and health as well as wanting and Nutri-Score (Table S13, Figures S31-S34). Importantly and in line with our PCA, these models yielded comparable results.

Parameter Estimation

Parameter estimation was targeted at testing differences across the two hunger state conditions. Specifically, we estimated a set of “baseline” parameters for the sated condition as well as the “change” in each parameter under hunger (i.e., $parameter_{hungry} = parameter_{sated} + \text{change}$). Following our previous work (Kraemer & Gluth, 2023), all group-level parameters were drawn from normal distributions $N(\mu, SD)$ and half-normal distributions $HN(\mu, SD)$ for group mean and group SD, respectively. More specifically, for the “baseline” parameters, the group mean and SD for α were drawn from $N(2, 1)$ and $HN(0, 3)$, respectively, the group mean and SD for nDT were drawn from $N(-1, 1)$ and $HN(0, 1)$, respectively, and the group mean and SD for all remaining parameters were drawn from $N(0, 0.5)$ and $HN(0, 0.5)$, respectively. For the “change” parameters, the group mean and SD for α and nDT were drawn from $N(0, 1)$ and $HN(0, 1)$, respectively, and the group mean and SD for all remaining parameters were drawn from $N(0, 0.25)$ and $HN(0, 0.25)$, respectively. On the participant-level, all individual parameters were drawn from normal distributions $N(\mu_{\text{group}}, SD_{\text{group}})$. Some of these parameter values were then soft-plus transformed (in case of α , nDT and σ) to enforce strictly positive values or phi-transformed (in case of β and ω) to enforce values between 0 and 1. In the *Results*, we report transformed parameter values which are easier to interpret, but untransformed values for the effect of hunger to illustrate deviations from 0. Hierarchical Bayesian parameter estimation (Farrell & Lewandowsky, 2018) was performed with JAGS, called within R using the R2jags package (Su & Yajima, 2021) and accelerated by parallel computing. We used piecewise constant averaging (Lombardi & Hare, 2021) to speed up model fit, in particular, of the (ma)DDMs and the mtDDM. For sampling, we used eight chains, with 60'000 iterations, 30'000 burnin samples and a thinning of 12, resulting in 2'500 samples per chain. Convergence was assessed via the Gelman-Rubin statistic (“Rhat”) (Gelman & Rubin, 1992) with a threshold of 1.05. Model fit was quantified with the Deviance Information Criterion (DIC) (Spiegelhalter et al., 2002). For our best-performing models (maaDDM, maaDDMsp, maaDDM2 ϕ , maaDDM2 ϕ sp), we performed posterior predictive checks, by drawing 1000 parameter values from the individual posterior parameter distributions, simulating

new data, and checking whether the empirical means fell into the 95% HDI of the simulated choice and RT data (see **Figure 4** [↗](#) and *Figure S17*). We implemented parameter recoveries of our best models (*Figure S18-S21*).

Acknowledgements

Sebastian Gluth was supported by the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation program (Grant agreement No. 948545). We would like to thank Soyoung Park for valuable discussions regarding our analyses and the study's implications, and to Stephanie Smith for inspirations on the model development. We thank Sophie Bavard and Chih-Chung Ting for providing useful feedback on our analyses. Finally, we would like to thank Polina Andonova, Anne-Christin Kaufmann, Susen Barth, and Stephanie Lehnert for their support with data collection.

References

- Banica I., Allison G., Racine S. E., Foti D., Weinberg A. (2023) **All the Pringle ladies: Neural and behavioral responses to high-calorie food rewards in young adult women** *Psychophysiology* **60** <https://doi.org/10.1111/psyp.14188>
- Barakchian Z., Beharelle A. R., Hare T. A. (2021) **Healthy decisions in the cued-attribute food choice paradigm have high test-retest reliability** *Scientific Reports* **11** <https://doi.org/10.1038/s41598-021-91933-6>
- Bates D., Mächler M., Bolker B., Walker S. (2015) **Fitting Linear Mixed-Effects Models Using lme4** *Journal of Statistical Software* **67**:1–48 <https://doi.org/10.18637/jss.v067.i01>
- Berkowitsch N. A. J., Scheibehenne B., Rieskamp J., Matthäus M. (2015) **A generalized distance function for preferential choices** *British Journal of Mathematical and Statistical Psychology* **68**:310–325 <https://doi.org/10.1111/bmsp.12048>
- 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 eyetracking** *Appetite* **76**:66–75 <https://doi.org/10.1016/j.appet.2013.11.021>
- Bucher T., Collins C., Rollo M. E., McCaffrey T. A., Vlieger N. D., Bend D. V. der, Truby H., Perez-Cueto F. J. A. (2016) **Nudging consumers towards healthier choices: A systematic review of positional influences on food choice** *British Journal of Nutrition* **115**:2252–2263 <https://doi.org/10.1017/S0007114516001653>
- Cameron J. D., Goldfield G. S., Finlayson G., Blundell J. E., Doucet É. (2014) **Fasting for 24 Hours Heightens Reward from Food and Food-Related Cues** *PLOS ONE* **9** <https://doi.org/10.1371/journal.pone.0085970>
- Charbonnier L., van Meer F., Johnstone A. M., Crabtree D., Buosi W., Manios Y., Androustos O., Giannopoulou A., Viergever M. A., Smeets P. A. M. (2018) **Effects of hunger state on the brain responses to food cues across the life span** *NeuroImage* **171**:246–255 <https://doi.org/10.1016/j.neuroimage.2018.01.012>
- Charbonnier L., van Meer F., van der Laan L. N., Viergever M. A., Smeets P. A. M. (2016) **Standardized food images: A photographing protocol and image database** *Appetite* **96**:166–173 <https://doi.org/10.1016/j.appet.2015.08.041>
- Chen P.-J., Antonelli M. (2020) **Conceptual Models of Food Choice: Influential Factors Related to Foods, Individual Differences, and Society** *Foods* **9** <https://doi.org/10.3390/foods9121898>
- Cheung T. T. L., Kroese F. M., Fennis B. M., De Ridder D. T. D. (2017) **The Hunger Games: Using hunger to promote healthy choices in self-control conflicts** *Appetite* **116**:401–409 <https://doi.org/10.1016/j.appet.2017.05.020>
- Dagher A. (2012) **Functional brain imaging of appetite** *Trends in Endocrinology & Metabolism* **23**:250–260 <https://doi.org/10.1016/j.tem.2012.02.009>

- Dalmajer E. S., Mathôt S., Van der Stigchel S. (2014) **PyGaze: An open-source, crossplatform toolbox for minimal-effort programming of eyetracking experiments** *Behavior Research Methods* **46**:913–921 <https://doi.org/10.3758/s13428-013-0422-2>
- Enax L., Krajch I., Weber B. (2016) **Salient nutrition labels increase the integration of health attributes in food decision-making** *Judgment and Decision Making* **11**:460–471 <https://doi.org/10.1017/S1930297500004563>
- 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**:221–227 [https://doi.org/10.1016/S0031-9384\(02\)00978-2](https://doi.org/10.1016/S0031-9384(02)00978-2)
- Eum B., Dolbier S., Rangel A. (2023) **Peripheral Visual Information Halves Attentional Choice Biases** *Psychological Science* **34**:984–998 <https://doi.org/10.1177/09567976231184878>
- Faul F., Erdfelder E., Buchner A., Lang A.-G. (2009) **Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses** *Behavior Research Methods* **41**:1149–1160 <https://doi.org/10.3758/BRM.41.4.1149>
- Fisher G. (2021) **A multiattribute attentional drift diffusion model** *Organizational Behavior and Human Decision Processes* **165**:167–182 <https://doi.org/10.1016/j.obhdp.2021.04.004>
- Führer D., Zysset S., Stumvoll M. (2008) **Brain Activity in Hunger and Satiety: An Exploratory Visually Stimulated fMRI Study** *Obesity* **16**:945–950 <https://doi.org/10.1038/oby.2008.33>
- Gabor A. M., Stojnic B., Ban Ostic D. (2020) **Effects of different nutrition labels on visual attention and accuracy of nutritional quality perception – Results of an experimental eye-tracking study** *Food Quality and Preference* **84** <https://doi.org/10.1016/j.foodqual.2020.103948>
- Garlasco P., Osimo S. A., Rumiati R. I., Parma V. (2019) **A hierarchical-drift diffusion model of the roles of hunger, caloric density and valence in food selection** *Appetite* **138**:52–59 <https://doi.org/10.1016/j.appet.2019.03.009>
- Gelman A., Rubin D. B. (1992) **Inference from Iterative Simulation Using Multiple Sequences** *Statistical Science* **7**:457–472
- Gluth S., Kern N., Vitali C. L. (2020) **Reply to: Divisive normalization does influence decisions with multiple alternatives** *Nature Human Behaviour* **4**:1121–1123 <https://doi.org/10.1038/s41562-020-00942-4>
- Gluth S., Spektor M. S., Rieskamp J. (2018) **Value-based attentional capture affects multi-alternative decision making** *eLife* **7** <https://doi.org/10.7554/eLife.39659>
- Hanßen R., Schiweck C., Aichholzer M., Reif A., Edwin Thanarajah S. (2022) **Food reward and its aberrations in obesity** *Current Opinion in Behavioral Sciences* **48** <https://doi.org/10.1016/j.cobeha.2022.101224>
- 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** *Journal of Neuroscience* **31**:11077–11087

- Hutcherson C. A., Tusche A. (2022) **Evidence accumulation, not “self-control,” explains dorsolateral prefrontal activation during normative choice** *bioRxiv* <https://doi.org/10.1101/2020.10.06.328476>
- Kraemer P. M., Gluth S. (2023) **Episodic Memory Retrieval Affects the Onset and Dynamics of Evidence Accumulation during Value-based Decisions** *Journal of Cognitive Neuroscience* **35**:692–714 https://doi.org/10.1162/jocn_a_01968
- Krajibich I. (2019) **Accounting for attention in sequential sampling models of decision making** *Current Opinion in Psychology* **29**:6–11 <https://doi.org/10.1016/j.copsyc.2018.10.008>
- Krajibich I., Armel C., Rangel A. (2010) **Visual fixations and the computation and comparison of value in simple choice** *Nature Neuroscience* **13**:1292–1298 <https://doi.org/10.1038/nn.2635>
- Lakens D., Scheel A. M., Isager P. M. (2018) **Equivalence Testing for Psychological Research: A Tutorial** *Advances in Methods and Practices in Psychological Science* **1**:259–269 <https://doi.org/10.1177/2515245918770963>
- Le S., Josse J., Husson F. (2008) **FactoMineR: An R Package for Multivariate Analysis** *Journal of Statistical Software* **25**:1–18 <https://doi.org/10.18637/jss.v025.i01>
- Lombardi G., Hare T. (2021) **Piecewise constant averaging methods allow for fast and accurate hierarchical Bayesian estimation of drift diffusion models with time-varying evidence accumulation rates** *PsyArXiv* <https://doi.org/10.31234/osf.io/5azyx>
- Maier S. U., Raja Beharelle A., Polanía R., Ruff C. C., Hare T. A. (2020) **Dissociable mechanisms govern when and how strongly reward attributes affect decisions** *Nature Human Behaviour* **4**:949–963 <https://doi.org/10.1038/s41562-020-0893-y>
- Malik S., McGlone F., Bedrossian D., Dagher A. (2008) **Ghrelin Modulates Brain Activity in Areas that Control Appetitive Behavior** *Cell Metabolism* **7**:400–409 <https://doi.org/10.1016/j.cmet.2008.03.007>
- Mathot S., Schreij D., Theeuwes J. (2012) **OpenSesame: An open-source, graphical experiment builder for the social sciences** *Behavior Research Methods* **44**:314–324 <https://doi.org/10.3758/s13428-011-0168-7>
- Mattson M. P. (2019) **An Evolutionary Perspective on Why Food Overconsumption Impairs Cognition** *Trends in cognitive sciences* **23**:200–212 <https://doi.org/10.1016/j.tics.2019.01.003>
- Mitchell N., Catenacci V., Wyatt H. R., Hill J. O. (2011) **OBESITY: OVERVIEW OF AN EPIDEMIC** *The Psychiatric clinics of North America* **34**:717–732 <https://doi.org/10.1016/j.psc.2011.08.005>
- NCD Risk Factor Collaboration (2016) **Trends in adult body-mass index in 200 countries from 1975 to 2014: A pooled analysis of 1698 population-based measurement studies with 19.2 million participants** *The Lancet* **387**:1377–1396 [https://doi.org/10.1016/S0140-6736\(16\)30054-X](https://doi.org/10.1016/S0140-6736(16)30054-X)
- Orquin J. L., Lahm E. S., Stojic H. (2021) **The visual environment and attention in decision making** *Psychological Bulletin* **147**:597–617 <https://doi.org/10.1037/bul0000328>
- Otterbring T. (2019) **Time orientation mediates the link between hunger and hedonic choices across domains** *Food Research International* **120**:124–129 <https://doi.org/10.1016/j.foodres.2019.02.032>

- Parker B. A., Sturm K., MacIntosh C. G., Feinle C., Horowitz M., Chapman I. M. (2004) **Relation between food intake and visual analogue scale ratings of appetite and other sensations in healthy older and young subjects** *European Journal of Clinical Nutrition* **58**:212–218 <https://doi.org/10.1038/sj.ejcn.1601768>
- Plassmann H., Schelski D. S., Simon M.-C., Koban L. (2021) **How we decide what to eat: Toward an interdisciplinary model of gut–brain interactions** *WIREs Cognitive Science* <https://doi.org/10.1002/wcs.1562>
- Rangel A. (2013) **Regulation of dietary choice by the decision-making circuitry** *Nature Neuroscience* **16**:1717–1724 <https://doi.org/10.1038/nn.3561>
- Ratcliff R. (1978) **A theory of memory retrieval** *Psychological Review* **85**:59–108 <https://doi.org/10.1037/0033-295X.85.2.59>
- Read D., van Leeuwen B. (1998) **Predicting Hunger: The Effects of Appetite and Delay on Choice** *Organizational Behavior and Human Decision Processes* **76**:189–205 <https://doi.org/10.1006/obhd.1998.2803>
- Rramani Q., Krajbich I., Enax L., Brustkern L., Weber B. (2020) **Salient nutrition labels shift peoples’ attention to healthy foods and exert more influence on their choices** *Nutrition Research* **80**:106–116 <https://doi.org/10.1016/j.nutres.2020.06.013>
- Schofield W. N. (1985) **Predicting basal metabolic rate, new standards and review of previous work** *Human Nutrition Clinical Nutrition* **39**:5–41
- Schomaker J., Vriens M., Jarva H. A. (2022) **Healthy or not: Influencing attention to bias food choices** *Food Quality and Preference* **96** <https://doi.org/10.1016/j.foodqual.2021.104384>
- Sepple C. P., Read N. W. (1989) **Gastrointestinal correlates of the development of hunger in man** *Appetite* **13**:183–191 [https://doi.org/10.1016/0195-6663\(89\)90011-1](https://doi.org/10.1016/0195-6663(89)90011-1)
- Shimojo S., Simion C., Shimojo E., Scheier C. (2003) **Gaze bias both reflects and influences preference** *Nature Neuroscience* **6**:1317–1322 <https://doi.org/10.1038/nn1150>
- Simonsohn U. (2015) **Small Telescopes: Detectability and the Evaluation of Replication Results** *Psychological Science* **26**:559–569 <https://doi.org/10.1177/0956797614567341>
- Spiegelhalter D. J., Best N. G., Carlin B. P., Van Der Linde A. (2002) **Bayesian measures of model complexity and fit** *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* **64**:583–639 <https://doi.org/10.1111/1467-9868.00353>
- Sullivan N. J., Huettel S. A. (2021) **Healthful choices depend on the latency and rate of information accumulation** *Nature Human Behaviour* <https://doi.org/10.1038/s41562-021-01154-0>
- Vriens M., Vidden C., Schomaker J. (2020) **What I see is what I want: Top-down attention biasing choice behavior** *Journal of Business Research* **111**:262–269 <https://doi.org/10.1016/j.jbusres.2019.09.001>
- Vuorre M., Bolger N. (2018) **Within-subject mediation analysis for experimental data in cognitive psychology and neuroscience** *Behavior Research Methods* **50**:2125–2143 <https://doi.org/10.3758/s13428-017-0980-9>

Weilbacher R. A., Krajbich I., Rieskamp J., Gluth S. (2021) **The influence of visual attention on memory-based preferential choice** *Cognition* **215** <https://doi.org/10.1016/j.cognition.2021.104804>

World Health Organization **Obesity and overweight**

Yang X., Krajbich I. (2023) **A dynamic computational model of gaze and choice in multi attribute decisions** *Psychological Review* **130**:52–70 <https://doi.org/10.1037/rev0000350>

Author information

Jennifer March

Department of Psychology and Hamburg Center of Neuroscience, Universität Hamburg, Hamburg, Germany

For correspondence: jennifer.march@uni-hamburg.de

Sebastian Gluth

Department of Psychology and Hamburg Center of Neuroscience, Universität Hamburg, Hamburg, Germany

Editors

Reviewing Editor

Thorsten Kahnt

National Institute on Drug Abuse Intramural Research Program, Baltimore, United States of America

Senior Editor

Joshua Gold

University of Pennsylvania, Philadelphia, United States of America

Reviewer #1 (Public review):

Summary:

In this article, the authors set out to understand how people's food decisions change when they are hungry vs. sated. To do so, they used an eye-tracking experiment where participants chose between two food options, each presented as a picture of the food plus its "Nutri-Score". In both conditions, participants fasted overnight, but in the sated condition, participants received a protein shake before making their decisions. The authors find that participants in the hungry condition were more likely to choose the tastier option. Using variants of the attentional drift-diffusion model, they further find that the best-fitting model has different attentional discounts on the taste and health attributes and that the attentional discount on the health information was larger for the hungry participants.

Strengths:

The article has many strengths. It uses a food-choice paradigm that is established in neuroeconomics. The experiment uses real foods, with accurate nutrition information, and incentivized choices. The experimental manipulation is elegant in its simplicity -

administering a high-calorie protein shake. It is also commendable that the study was within-participant. The experiment also includes hunger and mood ratings to confirm the effectiveness of the manipulation. The modeling work is impressive in its rigor - the authors test 9 different variants of the DDM, including recent models like the mtDDM and maaDDM, as well as some completely new variants (maaDDM2phi and 2phisp). The model fits decisively favor the maaDDM2phi.

Weaknesses:

First, in examining some of the model fits in the supplements, e.g. Figures S9, S10, S12, S13, it looks like the "taste weight" parameter is being constrained below 1. Theoretically, I understand why the authors imposed this constraint, but it might be unfairly penalizing these models. In theory, the taste weight could go above 1 if participants had a negative weight on health. This might occur if there is a negative correlation between attractiveness and health and the taste ratings do not completely account for attractiveness. I would recommend eliminating this constraint on the taste weight.

Second, I'm not sure about the mediation model. Why should hunger change the dwell time on the chosen item? Shouldn't this model instead focus on the dwell time on the tasty option?

Third, while I do appreciate the within-participant design, it does raise a small concern about potential demand effects. I think the authors' results would be more compelling if they replicated when only analyzing the first session from each participant. Along similar lines, it would be useful to know whether there was any effect of order.

Fourth, the authors report that tasty choices are faster. Is this a systematic effect, or simply due to the fact that tasty options were generally more attractive? To put this in the context of the DDM, was there a constant in the drift rate, and did this constant favor the tasty option?

Fifth, I wonder about the mtDDM. What are the units on the "starting time" parameters? Seconds? These seem like minuscule effects. Do they align with the eye-tracking data? In other words, which attributes did participants look at first? Was there a correlation between the first fixations and the relative starting times? If not, does that cast doubt on the mtDDM fits? Did the authors do any parameter recovery exercises on the mtDDM?

<https://doi.org/10.7554/eLife.103736.1.sa3>

Reviewer #2 (Public review):

Summary:

This study investigates the effect of a fed vs hungry state on food decision-making.

70 participants performed a computerized food choice task with eye tracking. Food images came from a validated set with variability in food attributes. Foods ranged from low caloric density unprocessed (fruits) to high caloric density processed foods (chips and cookies).

Prior to the choice task participants rated images for taste, health, wanting, and calories. In the choice task participants simply selected one of two foods. They were told to pick the one they preferred. Screens consisted of two food pictures along with their "Nutri-Score". They were told that one preferred food would be available for consumption at the end.

A drift-diffusion model (DDM) was fit to the reaction time values. Eye tracking was used to measure dwell time on each part of the monitor.

Findings:

Participants tended to select the item they had rated as "tastier", however, health also contributed to decisions.

Strengths:

The most interesting and innovative aspect of the paper is the use of the DDM models to infer from reaction time and choice the relative weight of the attributes.

Were the ratings redone at each session? E.g. were all tastiness ratings for the sated session made while sated? This is relevant as one would expect the ratings of tastiness and wanting to be affected by the current fed state.

Weaknesses:

My main criticism, which doesn't affect the underlying results, is that the labeling of food choices as being taste- or health-driven is misleading. Participants were not cued to select health vs taste. Studies in which people were cued to select for taste vs health exist (and are cited here). Also, the label "healthy" is misleading, as here it seems to be strongly related to caloric density. A high-calorie food is not intrinsically unhealthy (even if people rate it as such). The suggestion that hunger impairs making healthy decisions is not quite the correct interpretation of the results here (even though everyone knows it to be true). Another interpretation is that hungry people in negative calorie balance simply prefer more calories.

<https://doi.org/10.7554/eLife.103736.1.sa2>

Reviewer #3 (Public review):

Summary:

This well-powered study tested the effects of hunger on value-based dietary decision-making. The main hypothesis was that attentional mechanisms guide choices toward healthier and tastier options when participants are hungry and are in the fasted state compared to satiated states. Participants were tested twice - in a fasted state and in a satiated state after consuming a protein shake. Attentional mechanisms were measured during dietary decision-making by linking food choices and reaction times to eye-tracking data and mathematical drift-diffusion models. The results showed that hunger makes high-conflict food choices more taste-driven and less health-driven. This effect was formally mediated by relative dwell time, which approximates attention drawn to chosen relative to unchosen options. Computational modeling showed that a drift-diffusion model, which assumed that food choices result from a noisy accumulation of evidence from multiple attributes (i.e., taste and health) and discounted non-looked attributes and options, best explained observed choices and reaction times.

Strengths:

This study's findings are valuable for understanding how energy states affect decision-making and provide an answer to how hunger can lead to unhealthy choices. These insights are relevant to psychology, behavioral economics, and behavioral change intervention designs.

The study has a well-powered sample size and hypotheses were pre-registered. The analyses comprised classical linear models and non-linear computational modeling to offer insight into putative cognitive mechanisms.

In summary, the study advances the understanding of the links between energy states and value-based decision-making by showing that depleting is powerful for shaping the formation

of food preferences. Moreover, the computational analysis part offers a plausible mechanistic explanation at the algorithmic level of observed effects.

Weaknesses:

Some parts of the positioning of the hunger state manipulation and the interpretation of its effects could be improved.

On the positioning side, it does not seem like a 'bad' decision to replenish energy states when hungry by preferring tastier, more often caloric options. In this sense, it is unclear whether the observed behavior in the fasted state is a fallacy or a response to signals from the body. The introduction does mention these two aspects of preferring more caloric food when hungry. However, some ambiguity remains about whether the study results indeed reflect suboptimal choice behavior or a healthy adaptive behavior to restore energy stores.

On the interpretation side, previous work has shown that beliefs about the nourishing and hunger-killing effectiveness of drinks or substances influence subjective and objective markers of hunger, including value-based dietary decision-making, and attentional mechanisms approximated by computational models and the activation of cognitive control regions in the brain. The present study shows differences between the protein shake and a natural history condition (fasted, state). This experimental design, however, cannot rule between alternative interpretations of observed effects. Notably, effects could be due to (a) the drink's active, nourishing ingredients, (b) consuming a drink versus nothing, or (c) both.

<https://doi.org/10.7554/eLife.103736.1.sa1>

Author response:

Reviewer 1:

(1) We appreciate the reviewer's suggestion to test a multi-attribute attentional drift-diffusion model (maaDDM) that does not constrain the taste and health weights to the range of 0 and 1 and will test such a model.

(2) Similarly, we will follow the reviewer's suggestion to address potential demand effects. First, we will add "order" (binary: hungry-sated or sated hungry) as a predictor to our GLMM, to test for potential systematic effects of order on choices and response times. Second, we will split the participants by "order" and examine whether we see group differences of tasty and healthy decisions within the first testing session. Note that we already anticipate that looking at only 50% of the data and testing for a between-subject rather than within-subject effect is likely to reduce effect size and statistical sensitivity.

(3) We thank the reviewer for their observant remark about faster tasty choices and potential markers in the drift rate. While our starting point models show that there might be a small starting point bias towards the taste boundary which result in faster decisions, we will take a closer look at the simulated value differences as obtained in our posterior predictive checks to see if the drift rate is systematically more extreme for tasty choices.

(4) Regarding the mtDDM, we will verify that the relative starting time (rst) effects are minuscule. While we will follow the recommendation of correlating first fixations with rst, we would like to point out that a majority of fixations (see Figure 3b) and first fixations (see Figure S6b) are on food images. We will also provide a parameter recovery of the mtDDM.

Reviewer 2:

(1) We would like to verify the reviewer's interpretation that hungry people in negative calorie balance simply prefer more calories and would like to point to our supplementary

analyses, in which we show that hunger state also increases the probability of higher wanted and higher caloric decisions (see SOM4, SOM5, Figure S4). Moreover, we agree that high caloric items might not be unhealthy and are happy to demonstrate the correlations between health ratings and objective caloric content, to demonstrate the strong negative correlation in our dataset, which our principal component analyses hints at, too.

Reviewer 3:

(1) We agree that choosing tasty over healthy options under hunger may be evolutionarily adaptive. We will address the adaptiveness of this hunger driven mechanism in our discussion, reiterating the differentiation made in the introduction that this system no longer be adaptive in our obesogenic environment, leading to suboptimal decisions.

(2) We will address alternative explanations of the observed effects in our discussion with respect to the macro-nutritional content of the Shake and potential placebo effects arising from the shake vs no shake manipulation.

<https://doi.org/10.7554/eLife.103736.1.sa0>